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Optimization of overall equipment effectiveness (OEE) factors: Case study of a vegetable oil manufacturing company

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A B S T R A C T

The poor maintenance and usage of the equipment and machines of a vegetable oil manufacturing company adversely affect its competitive advantage. These industries are faced with numerous equipment maintenance challenges in the path to increasing their throughput as well as profitability. To address the said maintenance challenges, process data were obtained for the Overall Equipment Effectiveness (OEE) factors after their Total Productive Maintenance (TPM) implementation in the company. Minitab 21 software was used to analyze the data collected, and the results showed that the mean for quality, availability, and performance obtained were 96.929%, 63.35%, and 61.20%, respectively. This shows that the quality of products is the greatest OEE factor that vegetable oil manufacturing companies must consider meticulously to reduce the six big losses in their production processes. Response Surface Method (RSM) with Central Composite design, with the application of Design Expert 13 software, was used to model, analyze, and optimize the Overall Equipment Effectiveness (OEE) using availability, quality, and performance as the input parameters. The analysis of both the actual and coded values, which is the main contribution of the study, showed that quality has the greatest value followed by availability and performance. It was found that, to effectively reduce the six big losses, the quality, performance, and availability should be targeted as 98.3052%, 81.6022%, and 80.103%, respectively.

1. Introduction

Due to the lack of extraction technologies before the 20th century, refined vegetable oils were not readily available. These are extracted from plants using a chemical solvent or an oil mill. There is a growing demand for vegetable oil with increased population. Vegetable oil producers must respond swiftly to shifts in consumer demand, raw material availability, operational procedures, and technological improvements. The majority of manufacturing companies are working to increase and maximize their businesses' productivity in order to survive in the wide global market (Huang et al., 2003). As a result, the facility must have a reliable operating environment and maintenance system. The hardest part is meeting customers' expectations while maintaining a high profit margin at a cheap cost. To do this, every manufacturing company employs an efficient maintenance system that lowers machine downtime from unplanned stops and helps boost machine availability (Fore and Zuze, 2010; Muthiah et al., 2008). The productivity of a manufacturing plant is significantly harmed by equipment failures and inadequate availability. All of this happens because there is not any good maintenance mechanism in place. The percentage of effectiveness of industrial machinery or equipment is measured using a measure called overall equipment effectiveness (OEE). Performance rate, availability, and quality rate – which gauges equipment losses – are its three constituent parts. The

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implementation of an OEE plan would increase productivity in industrial firms by reducing equipment malfunction and downtime. According to the OEE index, all manufacturing companies' top priority is to increase the effectiveness of automated production lines (Zennaro et al.,2018). These days, manufacturing companies experience capacity constraints and either expand further or invest in new machinery. To increase equipment performance and dependability as well as reduce idle time, plants should optimize the efficiency of their current machinery (Aman et al., 2017; Kapuyanyika & Suthar, 2018).

But every piece of equipment needs to be handled efficiently to produce high-quality goods and manage demand (Nallusamy & Majumdar, 2017). Van Horenbeek et al. (2014) optimize the maintenance process by keeping an eye on the asset's condition. To maximize production capacity, condition data can be employed. The main goal of all manufacturing sectors is to maximize OEE value. This is accomplished by comparing the plant's operating performance to its ideal performance (Lanza et al., 2013). The production capacity is increased as a result of this improvement, and the downtime of the machine is decreased. Our study intends to increase profitability by enhancing OEE characteristics in a company that produces vegetable oil by identifying and reducing losses.

2. Literature Review

The OEE model (shown in **Fig. 1**) is popularly used for analyzing the OEE of a firm. It involves the upkeep, use, and administration of manufacturing resources and equipment (Jayaswal & Rajput, 2012). Losses are also found and eliminated with OEE. (Gupta et al., 2015; Hemanand et al., 2012). It captures fluctuations, which help to reduce equipment downtime through improved maintenance tasks (Zammori, 2014). OEE is a standard for evaluating the performance of a machine's subsystems and is used to increase a machine's efficiency (Nakhla, 2018). The efficiency of machinery can be enhanced; thus, steps are taken to boost its performance (Muthukumar & Thiruchitrambalam, 2020). It is an efficient method to compare actual manufacturing to what might be produced more efficiently (Muthumanickam, Thugudam, Ibne Hossain, et al., 2020; Corrales et al., 2020). An effective way of decreasing system downtime and maintenance costs is to find an optimal maintenance strategy (Daneshkhah et al., 2017). According to Okpala and Anozie (2018), OEE is a functional way of investigating equipment performance, considering major six big losses. Also, Lakho et al. (2020) employed Total Effective Upkeep (TEU), which begins with assessing General Device Effectiveness (OEE) and Six Substantial Losses. The research study identified the cause of the decreased OEE value, proposed a performance maintenance approach based on mean time between failures (MTBF) and mean time to repair (MTTR), and suggested total productive maintenance (TPM) implementation. TPM ameliorates operating conditions of equipment, helps to achieve the highest possible machine effectiveness with time, and maintains equipment at an optimal level of performance (Agustiady & Cudney, 2018; Ahuja & Khamba, 2008). Ihueze and U-Dominic (2017) focused on the usage of TPM strategies where the OEE metric has been followed to reduce the frequency of machine failures, thus improving production performance and operational efficiency of a manufacturing facility.

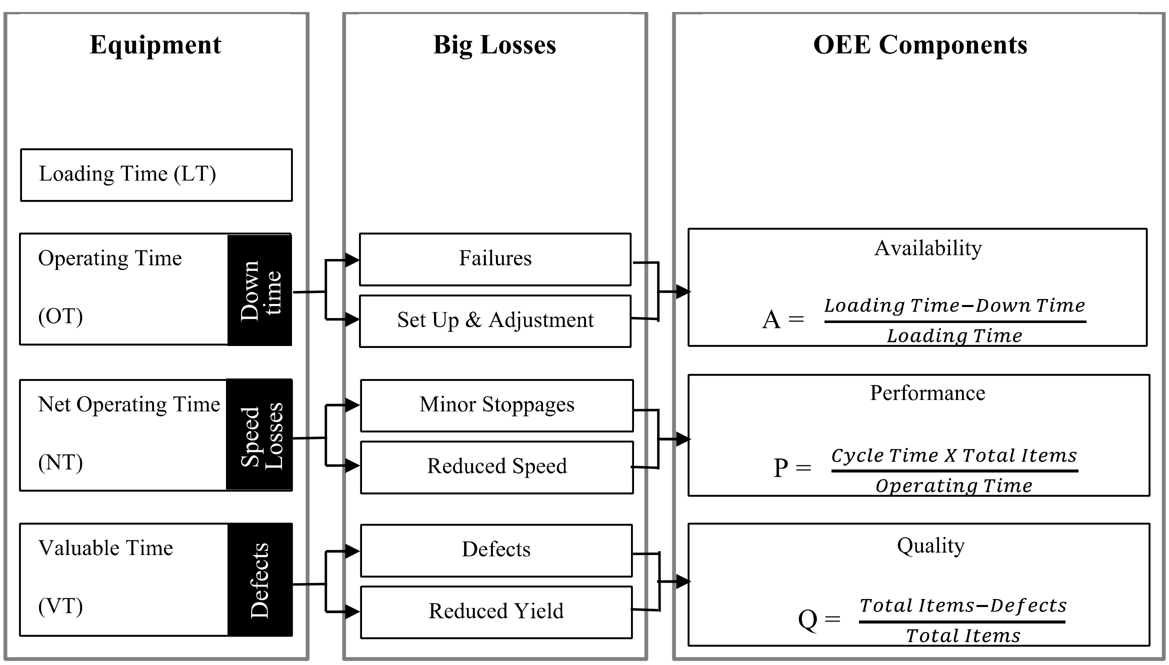

Fig. 1. The OEE model

According to Relkar and Nandurkar (2012), focusing on improving performance rates would result in a large increase in OEE. Optimization of OEE is more cost-effective to eliminate the negative impact of breakdown/downtime of a production floor. By improving OEE, production capacity and quality of products can be increased. Furthermore, downtime of machines will be decreased by enhancing the efficiency of the system. (Jeong and Phillips, 2001). The best parameters for achieving an OEE of 84.645% are 90% availability, 95% performance, and 99% quality. The OEE value of the autoclave process was improved by the implementation of time studies within the aerospace industry, where 4.64 percent of enlargement was for the availability ratio (Puvanasvaran et al., 2013). Ribeiro et al. (2019) used TPM methodology with some lean thinking tools aiming to optimize the availability of a production line producing mechanical components for the automotive industry where OEE, MTBF and MTTR were used to measure the success of the implemented actions. Abdul Rasib et al. (2019) used the Single Minutes Exchange of Dies (SMED) technique to improve the OEE of the automotive industry. "The results of the study revealed that the OEE of the industry has been increased by 2.7% after converting the internal activities to external activities for jig changes that were consuming a lot of time." VivekPrabhu et al. (2014) used the Genetic Algorithm in manufacturing systems to optimize the OEE. Salim and Rameshkumar (2016) improved the OEE of a CNC lathe machine from 31.21 percent to 74.47 percent after implementing TPM with extensive analysis and suggestions, which is still far below the world-class criteria. Abdelbar et al. (2019) suggested a new indicator of the OEE which can be used to assist maintenance managers to improve time, cost and quality of maintenance activities through a three-dimensional analysis. OEE enhances machine performance by recognizing relevant performance opportunities. Actually, it's the ratio of the actual output of equipment to its theoretical output (Okpala and Anozie 2018).

Nowadays, manufacturing companies are evolving alternatives to solve capacity problems such as extra shifts, purchasing new equipment, etc. An alternative approach is proposed by Aman et al. (2017) to enhance the performance of their existing equipment with respect to the machine reliability and operator's performance, where the OEE has gained much more attention in the recent past. In another study, Palanisamy & Vino. (2013), deployed the OEE concepts on a shop floor in a process industry. They investigated the bottleneck equipment through an IT integrated system and improved the OEE of the shop floor, which resulted in reducing the downtime from 29 hours to 31 hours with the help of different tools such as single-minute exchange of dies (SMED), preventive maintenance, and extension of time (EOT). This optimized production data.

OEE may be improved by reducing malfunctions and changeover losses associated with accessibility, as well as defects and setup scrap losses associated with high quality (Singh and Narwal, 2017). Nallusamy et al. (2018) showed that downtime losses aren't the only factor that influences overall equipment performance (OEE); time spent on a piece of equipment is another factor to consider. It is obvious that employing totally reliable maintenance lean gadgets such as JishuHozen, Kaizen, and others in a manufacturing organization may significantly improve section OEE. Lakho et al. (2020) and Virk et al. (2020) gave a comprehensive analysis of TPM and OEE in maintenance management operations across several industrial sectors, emphasizing their applications and advantages. Baghbani et al. (2019) reported a 6.05% increase in OEE for a sugar factory using fuzzy FMEA. Chikwendu et al. (2020) optimized the OEE factors for a pharmaceutical company. We adopt the research framework of their paper for our work.

We find that the OEE analysis and optimization was never performed for a real case study of any vegetable oil manufacturing company. In this paper, we seek to optimize the OEE factors of a vegetable oil manufacturing company using the actual process data. This is the unique and novel contribution of this research work.

3. Methodology

3.1 Case Study of the Company

The research was conducted at a Bangladeshi vegetable oil manufacturing facility with production sections of their mother product, Coconut Oil. With a variety of brands in several categories, the firm touches the lives of one out of every two Bangladeshis. Some of the products they make are: Super Premium Refined Edible Oil, Dry Fruit Oil, Ayurvedic Hair Oil, Coconut Oil, Olive Oil, Vitamin-E Oil, and Aloe Vera Enriched Coconut Hair Oil. Coconut Oil, on the other hand, is their hallmark product.

We collect the data from the filling unit at their factory after their TPM implementation. The process flowchart for the filling process is illustrated in **Fig. 2**. In the first stage, as bottles are placed into a big hopper at random, an unscrambler machine receives them in random places. The bottles are then handled in various ways and sorted until they reach a standing position on the conveyor leading to the bottle filler. In addition, IJP coding has been completed. Furthermore, an automatic filling system with 16 nozzles fills bottles with oil. Then, as a final step, auto capping is performed in the capping machine. Packaging, on the other hand, is done in a shrinking machine, a technique known as shrink wrapping. After that, the bottles are loaded into the CFC.

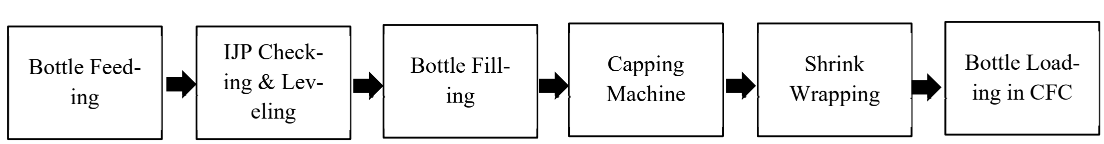

Fig. 2. Workflow of the Filling Unit

3.2 Data collection

In this work, we evaluate the OEE values of the filling section exclusively in order to optimize the OEE variables in a vegetable oil production company. From October 2019 to July 2021, data on the availability, performance, and quality of the filling section's machinery was collected for 22 months. This data aided us in determining the OEE values. The three OEE rates – availability, performance, and quality were calculated separately, and the OEE was calculated as the product of these three rates (shown in **Table 1**).

Table 1
OEE data table

Month	Availability (%)	Performance (%)	Quality (%)	OEE (%)
October 2019	57.32%	58.15%	99.55%	33.18%
November 2019	50.07%	49.96%	99.86%	24.98%
December 2019	57.78%	59.41%	98.56%	33.83%
January 2020	48.20%	49.84%	97.78%	23.49%
February 2020	66.14%	64.77%	97.82%	41.90%
March 2020	52.94%	51.40%	96.83%	26.35%
April 2020	41.51%	42.26%	94.59%	16.59%
May 2020	32.14%	31.29%	95.68%	9.62%
June 2020	46.26%	56.67%	98.67%	25.87%
July 2020	51.22%	54.16%	93.57%	25.95%
August 2020	68.24%	76.09%	96.65%	50.18%
September 2020	65.83%	64.90%	96.78%	41.35%
October 2020	70.20%	69.97%	96.62%	47.46%
November 2020	69.24%	70.86%	93.96%	46.10%
December 2020	69.17%	71.84%	94.89%	47.16%
January 2021	81.84%	79.09%	98.87%	63.99%
February 2021	76.28%	73.02%	97.65%	54.39%
March 2021	69.33%	71.04%	96.58%	47.57%
April 2021	76.76%	76.22%	95.34%	55.78%
May 2021	68.01%	76.79%	96.61%	50.45%
June 2021	72.42%	83.01%	97.29%	58.49%
July 2021	55.57%	62.95%	98.29%	34.39%

4. Results and Analysis

Using the data of Table 1, we perform some basic statistical analysis using Minitab 21. Next, we perform the response surface methodology (RSM) with Central Composite design- based optimization using the Design Expert 13 software. The findings are discussed in the next section.

4.1 Descriptive statistics

Descriptive statistics are used to summarize features of a data collection, such as the mean, standard deviation, or minimum and maximum of a variable, providing a statistical analysis of the system's parameters. As the analysis reveals (**Table 2**), the mean Availability, Performance, and Quality values are 61.20%, 63.35%, and 96.93%, respectively, yielding a mean OEE of 39.05%. Again, these three rates have ranges of [32.14%, 81.84%], [31.29%, 83.01%] and [93.57%, 99.86%], resulting in an OEE range of [9.62%, 63.99%].

Table 2
Descriptive Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Availability	0.6120	0.1275	0.3214	0.8184
Performance	0.6335	0.1313	0.3129	0.8301
Quality	0.96929	0.01735	0.93570	0.99860
OEE	0.3905	0.1454	0.0962	0.6399

4.2 Outlier test

A single outlier in a univariate data set with an almost normal distribution is detected using Grubbs' test. Significant outliers are those where the *p* value is less than 0.05. As shown by the table's *p* values (**Table 3**), which are all greater than 0.05, there is no outlier at the 5% level of significance.

Table 3
Outlier Test (Grubbs' Test)

Variable	N	Mean	Standard Deviation	Min	Max	G	P
Availability	22	0.6120	0.1275	0.3214	0.8184	2.28	0.341
Performance	22	0.6335	0.1313	0.3129	0.8301	2.44	0.191
Quality	22	0.96929	0.01735	0.93570	0.99860	1.94	0.976

4.3 One sample t-test

The One Sample t-test is used to see if a population's mean differs statistically from a known or hypothesized value. Additionally, it establishes the confidence range for the mean differences and demonstrates the relevance of the system's univariate parameters. Here, **Table 4** demonstrates the Availability, Performance and Quality all have higher mean differences as well as upper and lower confidence intervals of the differences (CIoD). A point estimate for the true mean OEE is 39.05%, and we are 95% confident that the true mean is between 32.60% and 45.50%.

Table 4
One-Sample t-test

Sample	N	Mean	Standard Deviation	SE Mean	95% CI for μ
Availability	22	0.6120	0.1275	0.0272	(0.5555, 0.6685)
Performance	22	0.6335	0.1313	0.0280	(0.5753, 0.6917)
Quality	22	0.96929	0.01735	0.00370	(0.96160, 0.97698)
OEE	22	0.3905	0.1454	0.0310	(0.3260, 0.4550)

4.4 Linear Regression Analysis

When a hypothesis is tested against observable data, a p-value is employed as a statistical measurement. Use of the p-value in the ANOVA output to determine whether the differences between some of the means are statistically significant. If the p-value is 0.05 or below, the result is recognized as statistically significant; nevertheless, if it is more than 0.05, the result is statistically insignificant and is more likely to be overlooked in silence. As can be seen from **Table 5**, quality is statistically insignificant in this case with a p value of 0.576, whereas availability and performance are statistically significant with a p value of 0.000.

Table 5
Linear Regression Analysis

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Regression	3	0.437542	0.145847	397.74	0.000
Availability	1	0.014709	0.014709	40.11	0.000
Performance	1	0.008225	0.008225	22.43	0.000
Quality	1	0.000119	0.000119	0.32	0.576

The amount of variance for a dependent variable that is explained by an independent variable is expressed statistically as R-squared. It can be observed from **Table 6** that 98.51% of the total variation in the dependent variable (OEE) can be explained by the variation in the independent variables (availability, performance, and quality).

Table 6
Model Summary

S	R-sq	R-sq(adj)	R-sq(pred)

0.0191491	98.51%	98.27%	97.08%

Linear regression analysis is a statistical technique for predicting the value of one variable on the basis of another. The sign of a regression coefficient tells us whether there is a positive or negative correlation between each independent variable and the dependent variable. We obtain the regression equation as follows:

$$\text{OEE (\%)} = -0.446 + 0.656 \text{ Availability (\%)} + 0.476 \text{ Performance (\%)} + 0.137 \text{ Quality (\%)}$$

4.5 Pearson Correlation

The Pearson correlation method is the most widely used approach for numerical variables, which assigns a number between 0 and 1, with 0 representing no correlation and 1 representing total positive correlation. Moreover, -1 represents the total negative correlation. According to the findings (**Table 7**), the strong positive correlation between availability and performance is significant in determining overall equipment effectiveness (OEE), although quality is not.

Table 7
Pearson Correlation: Availability (%), Performance (%), Quality (%, OEE (%)

	Availability	Performance	Quality
Performance	0.949		
Quality	0.017	0.024	
OEE	0.983	0.976	0.036

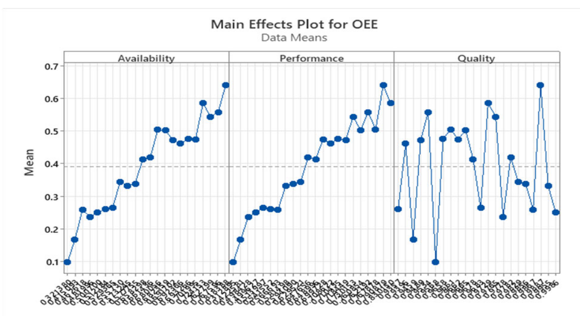

Fig. 3. Main Effects Plot

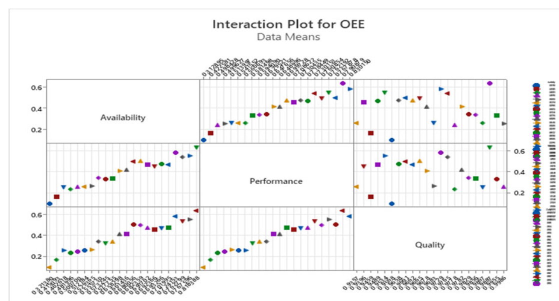

Fig. 4. Interaction Plot for OEE

4.6 Main Effects Plot

The main effects plot is the most basic graphical tool for determining the relative influence of various inputs on the desired output. This graph can be used to compare the relative strengths of several factors' effects. In this Main Effects Plot (**Fig. 3**), it appears that quality is associated with the highest mean strength. Although the results of the two-way ANOVA indicate that this main impact is statistically insignificant, the discrepancy may be due to random chance. Moreover, there is a noticeable increasing trend in availability and performance which is significantly affecting the OEE

4.7 Interaction Plot for OEE

Interaction plots are used to understand how the behavior of one variable depends on the value of another variable. Interactions occur when variables act together to impact the output of the process. The interaction plot (**Fig. 4**) shows that there is no interaction between quality and availability or performance. Rather, there is an interaction between availability and performance that is constructive.

4.8 Results from Design Expert analysis

Design Expert 13 is employed to design, evaluate, and utilize availability, quality, and performance to improve OEE characteristics. The input parameters are displayed in **Table 7** together with the input factor levels, means, and standard deviations for the system. They are displayed for the system's performance, quality, and availability. The model to use for the system's best optimal solutions was suggested in **Table 8**. From the model the 2FI: Sequential sum of squares for the two-factor interaction (AB, BC, etc.) terms was suggested for this model. The relevance of including interaction factors in the linear model is evaluated using the F-value. A low p-value (Prob>F) suggests that the model has been enhanced by the inclusion of interaction factors. The highest order polynomial where the additional components are important and the model is not aliased is chosen via sequential model sum of squares, as illustrated in **Table 9**. To find the best optimal solutions, the system, however, recommends using the model. The optimum solution criteria for the system are shown in **Table 10**. To optimize the ideal solution, it displays the upper and lower bounds of the input and output parameters.

Table 7

Statistical analysis of the input parameters

Factor	Name	Units	Type	SubType	Minimum	Maximum	Coded Low	Coded High	Mean	Std. Dev
A	Availability		Numeric	Continuous	0.3214	0.8184	-1↔1.00	+1↔1.00	0.6120	0.1275
B	Performance		Numeric	Continuous	0.3129	0.8301	-1↔1.00	+1↔1.00	0.6335	0.1313
C	Quality		Numeric	Continuous	0.9357	0.9986	-1↔1.00	+1↔1.00	0.9693	0.0173

Table 8

The summary of the selected model of the OEE

Source	Sequence p-value	Lack of Fit p-value	Adjusted R^2	Predicted R^2	
Linear	<0.0001		0.9827	0.9708	
2FI	**<0.0001**		**1.0000**	**1.0000**	**Suggested**
Quadratic	0.1054		1.0000	1.0000	
Cubic			1.0000		
Quartic					Aliased

Table 9

Sequential model sum of squares

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
Mean vs Total	3.35	1	3.35			
Linear vs Mean	0.4375	3	0.1458	397.74	<0.0001	
2FI vs Linear	**0.0066**	**3**	**0.0022**	**60105.48**	**<0.0001**	**Suggested**
Quadratic vs 2FI	2.133E-07	3	7.110E-08	2.54	0.1054	
Cubic vs Quadratic	3.357E-07	10	3.357E-08			
Quartic vs Cubic	0.0000	2	0.0000			Aliased
Residual	0.0000	0				
Total	3.80	22	0.1727			

Taking into account the actual components and disregarding the inconsequential numbers, the final OEE equation is as follows:

$$OEE = 0.3482 - 0.7724A - 0.4113B - 0.3620C + 0.9638AB + 0.8002AC + 0.4290BC$$

where Availability, Performance, and Quality are represented by A, B, and C respectively. For the predictions of response at given levels of each element the equation based on coded factors is applied. The high values of the factors are coded as +1, and their low levels are coded as -1. Correspondence factor coefficients can aid with factor identification to determine the relative impact of the coded equation.

Table 10

Final Equation in Terms of Coded Factors

OEE	=
+0.3482	
-0.7724	*A
-0.4113	*B
-0.3620	*C
+0.9638	*AB
+0.8002	*AC
+0.4290	*BC

Table 11

Criteria for optimal solutions in the system constraints

Name	Goal	Lower Limit	Upper Limit	Lower Weight	Upper Weight	Importance
A: Availability	is in rang	0.3214	0.8184	1	1	3
B: Performance	is in rang	0.3129	0.8301	1	1	3
C: Quality	is in rang	0.9357	0.9986	1	1	3
OEE	maximize	0.096214	0.639932	1	1	

Table 12

Optimal solution

Availability	Performance	Quality
0.80103	0.816022	0.983052

The influence of the input parameters on the output parameter is shown by the Desirability contour plots in **Fig. 5**. It demonstrates that raising performance standards will make something more desirable. The desirability will increase when availability and performance variables both rise, according to the Desirability contour plots in **Fig. 6**. The Desirability contour plot **Fig. 7** demonstrates the beneficial effect that availability growth has on desire.

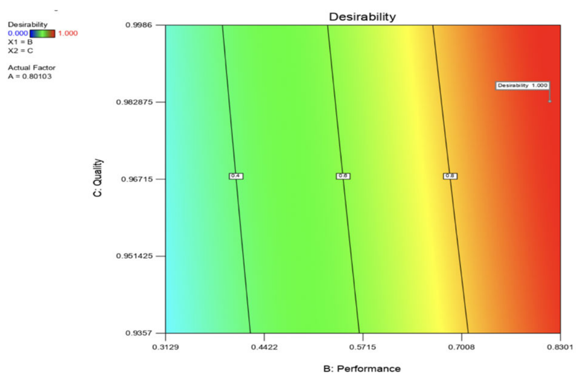

Fig. 5. Desirability contour plot – Quality vs Performance

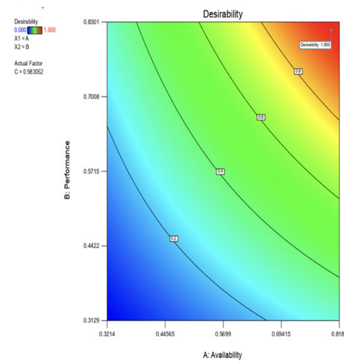

Fig. 6. Desirability contour plot – Performance vs Availability

OEE contour plot in **Fig. 8**, **Fig. 9**, and **Fig. 10** demonstrate that, given the independent variables' performance and availability or quality and availability or quality and performance parameters as inputs, the desirability of 100% occurs at 64.22% of the OEE. The influence of the input is seen by the contour plots of OEE. Increasing the performance and availability variable will raise the overall efficacy of the equipment, as shown by the relationship between the input and output parameters while variations in quality will not affect the final result so much.

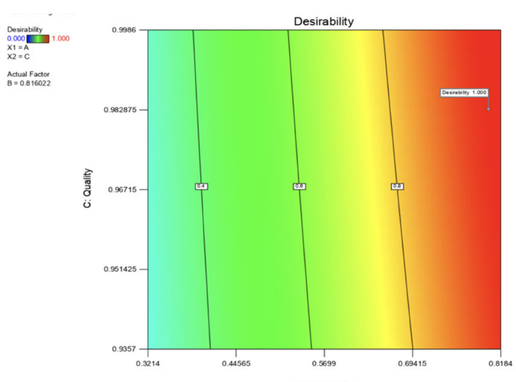

Fig. 7. Desirability contour plot – Quality vs Availability

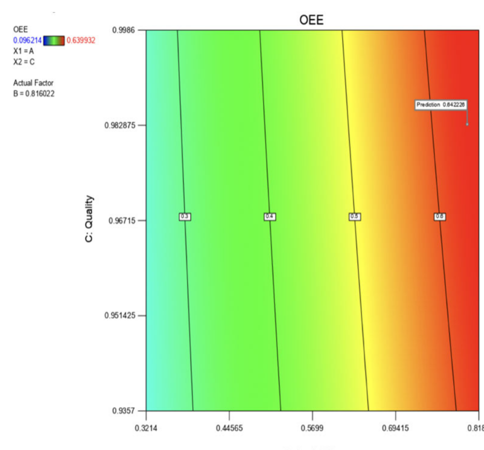

Fig. 8. OEE contour plot – Quality vs Availability

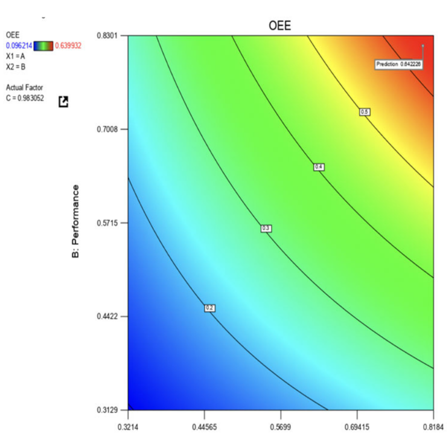

Fig. 9. OEE contour plot – Performance vs Availability

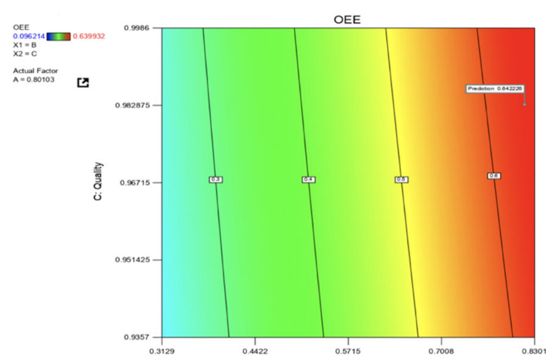

Fig. 10. OEE contour plot – Quality vs Performance

Response surface plot in **Fig. 11** illustrates how an increase in the availability and performance factors will improve the efficiency of the entire equipment. Furthermore, Response surface plot in **Fig. 12** and **Fig. 13** facilitate it to assess how performance and quality influence Overall Equipment Effectiveness (OEE). The response surface method also showed that quality has the greatest value followed by availability and performance. Additionally, the results of Minitab 21 are validated by the maximum values for all three OEE criteria, with quality, availability, and performance percentage values of 98.3, 80.1, and 81.6, respectively.

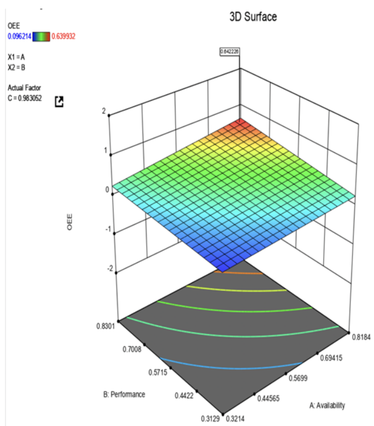

Fig. 11. 3D Response surface plot – Performance vs Availability

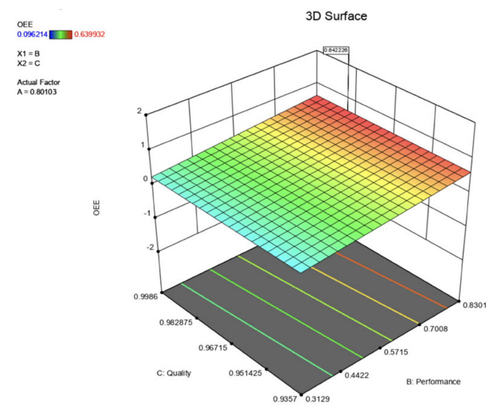

Fig. 12. 3D Response surface plot – Quality vs Performance

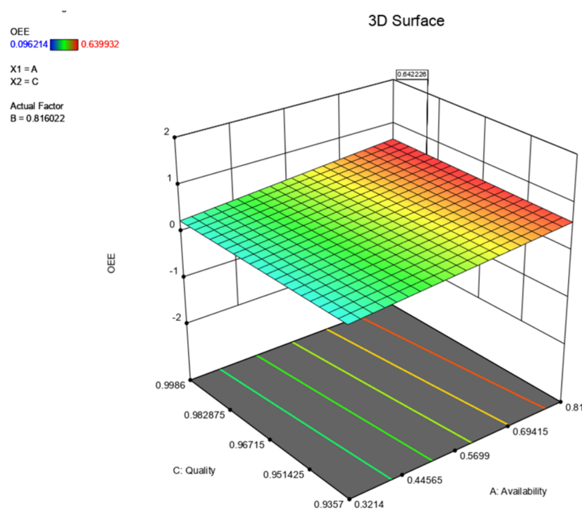

Fig. 13. 3D Response surface plot – Quality vs Availability

5. Conclusion

A full integration of the total productive maintenance (TPM) program places a strong emphasis on performance enhancement, which optimizes the company's efficiency of equipment. The study finds that using the OEE approach within organizations aids in increasing equipment efficiency. OEE is a useful platform for organization to grow improvement opportunities because it measures TPM. For OEE to be continuously improved and yield positive results, it requires participation from all levels of management, from workforce to production line workers.

In this study, we evaluate the OEE of the vegetable oil manufacturing company using their components. Data collection for 22 periods (months) on the availability, performance, and quality of the filling section's machinery helped us determine the OEE values, where it ranges from 9.62% to 63.99%. To understand the OEE indicators, the collected data were studied. The results were analyzed by Minitab 21 software. The use of this software enabled the display of the effects of availability, quality, and performance on the response OEE, respectively. Additionally, it displays how the input variables interact and determines whether any outliers (data point that differs significantly from other observations) exist. Although the company's OEE factors show efficiency, there is still opportunity for further efficiency, which is why optimization is necessary. For that reason, we use Design Expert 13 program to assesses and optimize OEE employing input factors (performance, quality, and availability). It improves OEE value by improving and utilizing all three OEE criteria. And the optimal solution for all three OEE criteria, percentage values are 98.3, 80.1, and 81.6, respectively. And we may get the optimal OEE value of 64.3% by preserving these values in the OEE criterion.

Thus, it can be observed that OEE is a crucial performance measurement tool that takes into account the overall influence of all plant components. The variable availability, quality, and performance factors that lower OEE were discovered, and appropriate alterations through optimization were carried out, leading to a significant improvement in OEE. The significance of this research's findings is that they now enable the interpretation of production line productivity by OEE, and the proposed methodology is very impactful in discovering concerns and observing the interaction between OEE criteria and the underlying advancements required to enhance productivity for a vegetable oil manufacturing company.

Disclosure Statement

The authors declare that they have no potential conflict of interest or financial conflict to disclose.

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