Evaluation and Optimization of Costs for Agricultural Machinery Management System in Arjo Diddessa Sugar Factory

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Abstract

Efficient control of agricultural machinery is crucial in sugar plants for maintaining product quality, managing operational costs, and improving productivity. The Ethiopian sugar industry is vital to the country's economy; however, issues with machinery management can lead to higher maintenance costs and poor operational efficiency. This study aims to evaluate the agricultural machinery management system at the *Arjo Diddessa* sugar factory and optimize operational costs. Between 2016 and 2022, data were collected through surveys, interviews, and observations. To improve machinery running costs, a linear programming model was studied using Linear Interactive and Discrete Optimizer (LINDO) software. The findings revealed that 49% of non-operational machinery required minor repair, whereas 14% required disposal. The anticipated work rate exceeded the actual rate by 35.33%. Among the tasks, uprooting exhibited the smallest variance at 5.73%, while inter-row cultivation displayed the greatest discrepancy at 67.21%. Initial repair expenses were minimal but increased as the equipment aged. The optimization model achieved a maximum reduction of 10.60% in operational costs during 2021-22, highlighting the importance of accurate machinery work rate estimation and performance analysis for enhancing efficiency. The study identified critical inefficiencies in machinery management and emphasized the need for robust maintenance systems and strategic replacement plans for aging equipment. Optimizing operational efficiency is essential for improving productivity and reducing costs in sugar production processes.

Keywords: Machinery field capacity, Maintenance performance, Machinery management system, Operational efficiency

Introduction

The Ethiopian sugar industry is a pillar of the country's agricultural and industrial sectors, playing a critical role in its socioeconomic growth. This industry not only provides a large number of jobs but also contributes significantly to national revenue and food security (Gebeyehu & Abbink, 2022). Its wide-ranging impact is its relevance to Ethiopia's overall economic structure (Zikargie, Wisborg, & Cochrane, 2023). The Ethiopian sugar industry is pivotal to the nation's agricultural and industrial sectors, significantly contributing to socioeconomic development, job creation, and food security (Zikargie, Wisborg, & Cochrane, 2022). Despite its importance, the sugar industry faces challenges, particularly in agricultural machinery management (Gebreeyessus, Mekonnen, Chebude, & Alemayehu, 2021). Poor management of agricultural machinery can severely impact operational efficiency, resulting in higher maintenance and repair costs, increased fuel consumption, and a reduced lifespan for equipment. These problems collectively hinder productivity and profitability, underlining the need for effective machinery management strategies (Kolhe, Lemi, & Busse, 2024).

The efficient management of agricultural machinery within this industry directly affects operational efficiency, productivity, and cost control. Studies underscore that suboptimal machinery management leads to elevated maintenance expenses, reduced equipment lifespan, and higher fuel consumption, thereby diminishing profitability (Ayele Zikargie & Cochrane, 2024).

Addressing these challenges requires innovative strategies tailored to the unique dynamics of Ethiopia's sugar industry.

Research indicates that the integration of modern maintenance practices, such as predictive and preventive maintenance, can significantly mitigate operational inefficiencies (Nunes, Santos, & Rocha, 2023). For example, incorporating real-time monitoring and advanced diagnostic tools has been shown to reduce downtime and improve machinery utilization rates (Pejić Bach, Topalović, Krstić, & Ivec, 2023). Moreover, operator training programs focusing on machinery calibration and fuel-efficient practices play a critical role in maintaining equipment longevity and achieving operational excellence (Firoozi, Tshambane, Firoozi, & Sheikh, 2024). In the context of large-scale agricultural operations, optimization models like linear programming have proven effective in balancing cost reduction with machinery performance (Boninsenha, Mantovani, Costa, & da Silva Júnior, 2022).

Establishing a comprehensive machinery management plan is critical to improving inefficient agricultural machinery management (Papageorgiou, 2015). This plan includes regular and preventive maintenance schedules to decrease downtime and repair costs, fuel-efficient practices to minimize consumption, and systematic equipment performance tracking to identify underperforming machinery for timely replacement. Proper agricultural machinery management requires a holistic approach that includes regular maintenance, timely repairs, and strategic replacement of outdated equipment (Ambo, 2024). This is crucial in mechanized agriculture, where the costs associated with purchasing and operating machinery are significant (Rahman *et al.*, 2021; Zhang, Yang, Wang, & Twumasi, 2023).

Efficient agricultural machinery management involves regular maintenance, accurate calibration, operator training, and proactive repairs, which significantly extend equipment lifespan and maintain top performance (Salawu *et al.*, 2023). Maintenance procedures guarantee that potential issues are addressed before they lead to catastrophic breakdowns, reducing downtime and keeping equipment functioning smoothly (Abbasi, Martinez, & Ahmad, 2022). Hence, this study focuses on evaluating the current machinery management practices at the Arjo Diddessa sugar factory and proposes cost-reduction solutions to improve efficiency and productivity.

Materials and Methods

Study Area Description

The study area is located in Southwestern Ethiopia, specifically within the Oromia Regional State, and encompasses the Eastern Wollega, Ilu Aba Bora, and Jimma Zones. It is 540 kilometers from the capital along the Addis Ababa-Jimma-Nekemte Road. The site is 1,350 meters above mean sea level. It is located at 7°36'00" to 9° 36' 00" North and 35°32'00" to 37° 34' 00" East. The study area has a mean annual rainfall of 1400 millimeters. The rainy season extends from May until October. The monthly mean maximum temperature ranges from 21.16°C to 33.75°C, while the monthly mean minimum temperature ranges from 7.01°C to 14.89°C. Rainfall is insufficient, with no rain for four to five months continuously, while in some months, there is constant rain, primarily during the summer season (Fig. 1) (Ashine, Tilahun Ashine, Yesuf, & Bokke, 2022).

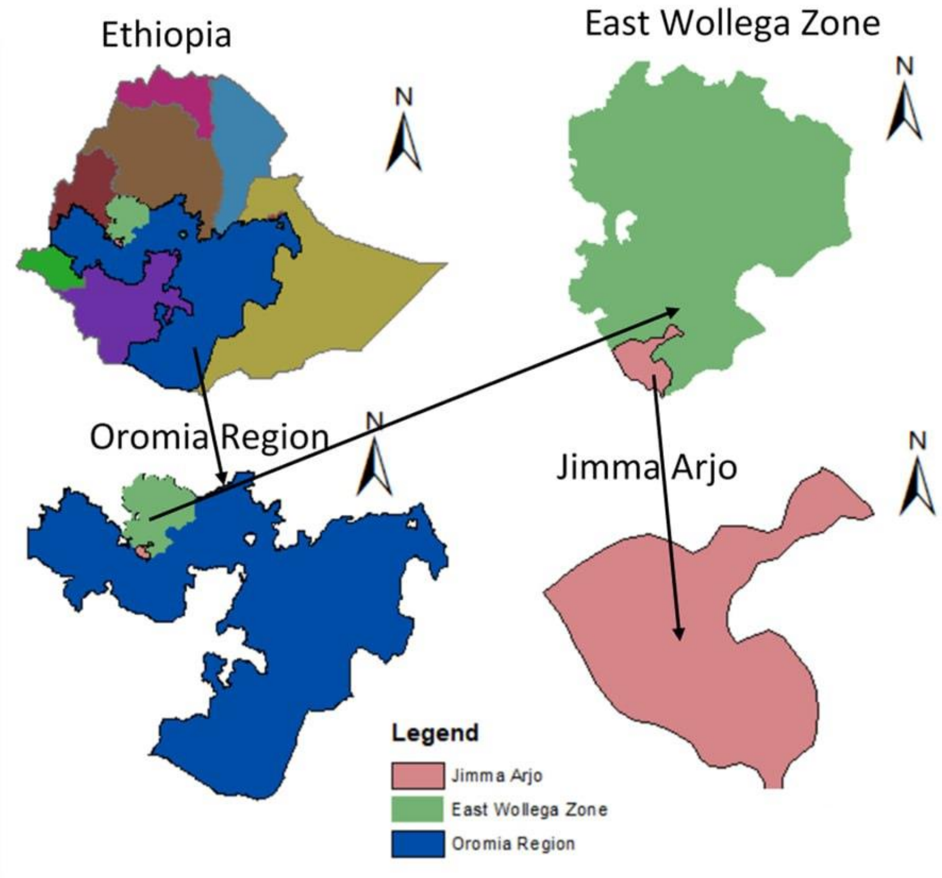

Fig. 1. Study area description map

Data Collection

The required input data for the machinery programming was collected for six seasons, namely 2016-2017 to 2021-2022, from both primary and secondary sources through semi-structured questionnaires, interviews, and observation surveys. Primary data were collected using formal and personal contacts from Arjo Diddessa sugar factory. These data include typical field working speeds (km h^{-1}), recommended field operations efficiency (%), machine width, and local purchase prices. The information also encompasses the types and sizes of available machinery and tractors, the type of field operations, machinery capacity (output), daily working hours, cost of field operations per hectare, fuel consumption, and the service life of tractors and machines. Secondary data were collected from various relevant documents, such as published and unpublished documents, bulletins, operation manuals and specifications sheets of machinery and tractors, agricultural operations scheduling programs, internal periodical reports, and the most relevant national and international published data. Additionally, both quantitative and qualitative data were collected for this study. Quantitative data, which can be quantified and represents any quantity, number, or percentage, were collected. Qualitative data, expressing any quality such as goodness, fairness, badness, and sufficiency, were also gathered.

Data Analysis Methods

Microsoft Excel was utilized to analyze the relationships between various variables and parameters, including machinery work rates, cost components, and optimization scenarios. Linear programming techniques were applied to optimize the operational costs of farm machinery using LINDO (Linear Interactive and Discrete Optimizer) software. The optimization model was constructed based on the gathered data and associated cost parameters. Analysis of Variance (ANOVA) was employed to demonstrate simple relationships and compare different variables. The collected data were interpreted and presented through tables, pie charts, bar graphs, and regression graphs. To address the research problem and findings, the data interpretation utilized descriptive methods, such as calculating percentages and average values, alongside statistical methods for deeper analysis. This structured approach not only facilitated a comprehensive understanding of the data but also highlighted key insights into machinery performance and cost management strategies within the agricultural context of the study. The combination of visual aids and statistical analysis provided a robust framework for evaluating operational efficiency and identifying areas for improvement in machinery management practices.

Sampling Techniques

The study considered all available farm machinery, including tractors and implements, at the Arjo Diddessa sugar factory. Different sampling techniques were used to calculate sample size based on study objectives and design. According to Etikan and Babatop (2019), a popular formula for computing sample size in survey research from a finite population is the formula shown as follow:

$$X = \frac{\left(Z^2.P.(1-P)\right)}{E^2} \quad (1)$$

where, X is the sample size, P is the proportion of the sample (typically 50% or 0.5), Z is the Z-score for the desired confidence level (1.96 for a 95% confidence interval), and E is the margin of error (0.05).

For a finite population, the adjusted sample size is determined as:

$$n = \frac{(N.X)}{(X+N-1)} \quad (2)$$

where, n is the adjusted sample size, N is the total population size, and X is the initial sample size.

For a population of 47, this calculation results in an initial sample size (X) of 384 and an adjusted sample size (n) of 42. Respondents from the land preparation, cultivation, and maintenance departments of Arjo Diddessa sugar factory were randomly selected to complete structured questionnaires on machinery management. Out of 42 participants, 26 (62%) completed the questionnaire, with 10 from land preparation and cultivation and 16 from maintenance.

Actual effective field capacity (AEFC), defined as the actual rate of area covered during the actual harvesting time, is a function of the machine's rated width and was calculated using the following formula (Yaseen *et al.*, 2024):

$$\text{AEFC} = \frac{year\ cultivated(\text{ha})}{annual\ hours(\text{hr})} \quad (3)$$

Theoretical field capacity, expressed in hectares per hour, is the rate of field coverage achieved if the weeder operates without interruptions, based on its theoretical width and speed, and is determined as follows (Fahmida *et al.*, 2024):

$$\text{TFC} = \frac{W(\text{m})\times S(\text{km hr}^{-1})}{10} \quad (4)$$

According to Zhang *et al.* (2024), the effective field capacity (EFC) of the machine, expressed in hectares per hour, was calculated using Equation 5 by recording the time required to cover a unit area, including the time spent lifting and lowering the equipment as well as turning the machinery.

$$\text{CEFC} = \frac{W(\text{m})\times S(\text{km hr}^{-1})\times FE(\%)}{10} \quad (5)$$

Optimization Model for Operational Cost

Similarly, the model was used in agriculture to maximize crop patterns and resource allocations (water, land, fertilizers, etc.) (Kalwar, Khan, Shahzad, Wadho, & Marri, 2022). According to Jupiara *et al.* (2024), linear programming is a field that applies scientific methods to solve control and optimization problems, such as agricultural system management, by providing more effective solutions aimed at maximizing profits and minimizing costs while taking into account the context's specific constraints. In addition, Bhamare (2023) emphasizes the application of mathematical programming techniques, namely linear programming, problems, applications, and models connected to the agro-industrial sector.

Linear programming (LP) is a mathematical strategy used in agriculture to optimize resource allocation, productivity, and profitability, particularly while operating agricultural machines (Oladejo, Abolarinwa, & Salawu, 2020). This strategy is crucial for resource management and cost reduction. The six years (2016/17-2012/22) fiscal working decision variable and operational cost expenses were modeled as an optimization problem (linear programing model). Thus, the objective function of the optimization problem is expressed in Eq. 6:

$$Minimize\ Costs,\ Z = a_{1T}RM_T + a_{2T}O_{pT} + a_{3T}F_{uT} + a_{4T}L_{uT} + a_{5T}S_{pT} \quad (6)$$

Subject to the linear constraints (s.t)

$a_{11}RM_1 + a_{12}Op_1 + a_{13}Fu_1 + a_{14}Lu_1 + a_{15}Sp_1 \geq X_1$

$a_{21}RM_2 + a_{22}Op_2 + a_{23}Fu_2 + a_{24}Lu_2 + a_{25}Sp_2 \geq X_2$

$a_{31}RM_3 + a_{32}Op_3 + a_{33}Fu_3 + a_{34}Lu_3 + a_{35}Sp_3 \geq X_3$

$a_{41}RM_4 + a_{42}Op_4 + a_{43}Fu_4 + a_{44}Lu_4 + a_{45}Sp_4 \geq X_4$

$a_{51}RM_5 + a_{52}Op_5 + a_{53}Fu_5 + a_{54}Lu_5 + a_{55}Sp_5 \geq X_5$

$a_{61}RM_6 + a_{62}Op_6 + a_{63}Fu_6 + a_{64}Lu_6 + a_{65}Sp_6 \geq X_6$

where, a_{1T} = Total repair and maintenance cost per six years

a_{2T} = Total operator costs per six years

a_{3T} = Total fuel costs per six years

a_{4T} = Total lubricant costs per six years

a_{5T} = Total spare part costs per six years, the detail notation is shown in the appendix.

$RM_1, RM_2, \ldots, RM_T; Op_1, Op_2, \ldots, Op_T; Fu_1, Fu_2, \ldots, Fu_T; Lu_1, Lu_2, \ldots, Lu_T; Spp_1, Spp_2, \ldots, Spp_T$ = Vector variable to determine the objective function value.

Eq. 7 can also be expressed in standard canonical form as:

Optimize (Min) $Z = \sum_{j=1}^{6} FCjXj + \sum_{i=1}^{6} Si \quad (7)$

Subject to the linear constraints

$\sum_{j=1}^{n} aij\ xj = b_i$, i = 1, 2, …, m, and $X_j, S_i \geq 0$ (for all i and j)

whereas;

$S_1, S_2, \ldots, S_6$ = Slack or surplus variables

$X_1, X_2, \ldots, X_6$ = Total operational costs of each year (from 2016/17-2021/22)

Z = Measure of performance which can be either profit or costs.

The research employed linear programming software (LINDO) to optimize the operational costs of agricultural machinery at the Arjo Diddessa sugar factory.

Results and Discussion

Agricultural Machinery Status in Arjo Diddessa Sugar Factory

While previous analyses have optimized the status of agricultural machinery, the introduction of new machines and technical advancements has significantly increased their usage. As a result, a current optimization was needed (Diez de Bonilla-Jiménez, Chávez-Mejía, Navarro-González, Ruiz-Velázquez, & Molina-Valencia, 2024; Sun, Zhang, Chen, & Qiao, 2023). The results of the study about the status of agricultural machinery at the Arjo Diddessa sugar factory shed light on the facility's operating efficiency and problems. The Factory has a total of 174 agricultural machinery, including tractors and tools. Only 37% of the machinery is functional, while 49% requires maintenance, and 14% needs disposal (Fig. 2). The fact that over half of the machinery is not working implies a significant maintenance backlog, which might be caused by a variety of factors, such as insufficient maintenance workers, a lack of spare parts, or inappropriate maintenance schedules. Regular maintenance is critical since neglected machinery is more likely to fail, resulting in greater downtime and lower output.

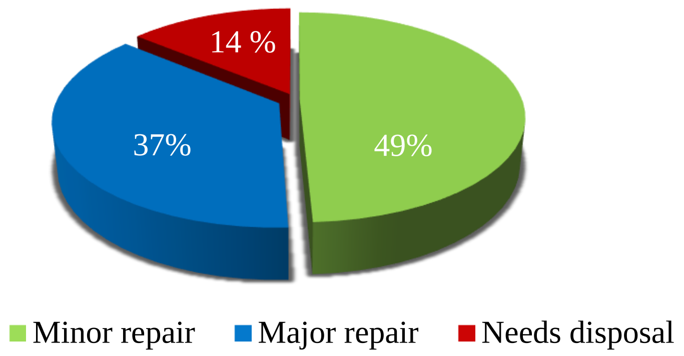

Fig. 2. Non-functional machinery at the Arjo Diddessa sugar factory

Moreover, the high rate of non-functional machinery likely contributes to operational inefficiencies and increased costs. Delays in critical farming operations such as planting and harvesting can adversely affect sugarcane yield and quality. Furthermore, operating poorly maintained machinery can lead to higher fuel consumption, exacerbating operational costs. This backlog could be due to several factors, such as insufficient maintenance staff, lack of spare parts, or inadequate maintenance planning. Addressing this issue is crucial, as machinery that is not regularly maintained is more prone to breakdowns and reduced performance. Implementing a comprehensive maintenance management system that includes preventive maintenance schedules and timely repairs is essential to address these challenges. Additionally, investing in training for maintenance staff and ensuring the availability of necessary spare parts will enhance the factory's operational capabilities. This strategy ensures that the factory operates with reliable and efficient machinery, minimizing downtime and unexpected failures (Salawu *et al.*, 2023).

The high percentage of non-functional and poorly maintained machinery likely contributes to operational inefficiencies, increased costs, and lower productivity. For instance, non-functional machinery can cause delays in critical farming operations, such as planting and harvesting, which can affect the overall yield and quality of the sugarcane. Additionally, operating machinery that is in poor condition can lead to higher fuel consumption and more frequent breakdowns, further escalating operational costs (Shaheb, Venkatesh, & Shearer, 2021).

Comparing the Calculated and Actual Rates of Work for Different Implements

The study compared the calculated and actual rates of work for different agricultural implements used at the factory. The results showed that the calculated rate of work was 35.33% higher than the actual rate. The implement with the least variation between calculated and actual rate was uprooting (5.73%), while inter-row cultivation had the most variation (67.21%). The estimated and actual rates of work for the various field forward speeds and operations performed at the factory were assessed, as shown in Table 1. The data presented in the table outlines the operational parameters for various agricultural implements used at the Arjo Diddessa sugar factory, including their width, hours of operation, speed, and effective field capacities.

The table includes several operations: bush cleaning, ripping, uprooting, deep plowing, harrowing, furrowing, and inter-row cultivation. Each operation is associated with specific machinery, indicating the implement type used for that task. The width of the implements varies from 2.1 m for bush cleaning and ripping to 6 m for harrowing. Wider implements typically allow for greater coverage per pass, which can enhance efficiency. The number of hours each implement operates varies significantly. For instance, bush cleaning operates for 1,393.16

hours, while ripping only operates for 141.44 hours. This disparity suggests that certain operations are prioritized over others based on seasonal requirements or operational strategies. The speed of operation ranges from 3 km h^{-1} for ripping to 8 km h^{-1} for furrowing. Higher speeds can lead to increased productivity; however, they must be balanced with the quality of work performed.

Table 1- Calculated and actual rate of work for different implements

Operations	Implement	Width (m)	Hours	Speed (km h^{-1})	A.E.F.C (ha h^{-1})	T.F.C (ha h^{-1})	FE%	C.E.F.C (ha h^{-1})	Variation (%)
Bush cleaning	Shanks	2.1	1,393.16	4	0.57	0.84	85	0.71	19.72
Ripping	Shanks	2.1	141.44	3	0.45	0.63	85	0.54	16.67
Uprooting	Disc plow	4	262.4	6	1.6	2.4	80	1.92	16.67
Deep plowing	Disc plow	4.5	1,019.60	5	1.8	2.3	85	1.91	5.73
Harrowing	Disc harrow	6	202.78	7	2.3	4.2	80	3.36	36.11
Furrowing	Furrower	4.35	862.92	8	1.43	1.16	85	2.96	51.67
Inter-row cultivation	Disc ridger	4.35	888.54	7	0.8	1.02	80	2.44	67.21

Fig. 3 compares the calculated and actual work rates for various agricultural implements at the and performance of the machinery used in operations. Fig. 3 illustrates that the calculated effective field capacity (CEFC) (ha h^{-1}) is consistently higher than the actual effective field capacity (AEFC) (ha h^{-1}) for all implements assessed. This discrepancy indicates that while theoretical calculations suggest optimal performance, practical conditions significantly impact operational efficiency. The calculated work rate was 35.33% higher than the actual rate, highlighting a substantial gap between expected and realized productivity.

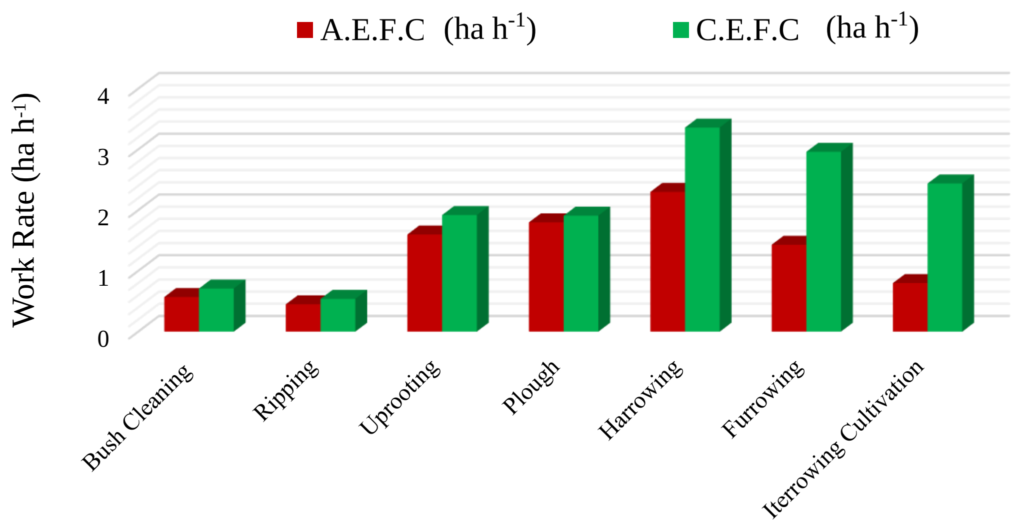

Fig. 3. Calculated and actual rate of work for different implements

In the case of implement performance, harrowing exhibited the highest calculated field efficiency at 3.36 ha h^{-1}, with an actual field efficiency of 2.3 ha h^{-1}, indicating effective performance under ideal conditions. Furrowing followed with a calculated rate of 2.96 ha h^{-1} and an actual rate of 1.43 ha h^{-1}, demonstrating good efficiency as well. The inter-row cultivation recorded an actual work rate of 0.8 ha h^{-1}, significantly lower than its calculated rate of 2.44 ha h^{-1}, while uprooting achieved an actual rate of 1.6 ha h^{-1} compared to a calculated rate of 1.92 ha h^{-1}, highlighting notable discrepancies likely due to operational inefficiencies, varying field conditions, and the unique characteristics of each implement. Conversely, ripping had the lowest rates, with a calculated rate of 0.54 ha h^{-1} and an actual rate of 0.45 ha h^{-1}, suggesting that this operation may be particularly challenging or inefficient.

Fig. 3 highlights notable variations in performance across different operations. Uprooting exhibited the least variation between calculated and actual rates, with only a 5.73% difference, suggesting this operation is performed consistently. In contrast, inter-row cultivation displayed the highest variation at 67.21%, indicating potential inefficiencies or inconsistencies in this process, possibly due to factors such as soil conditions or operator experience. The observed differences between calculated and actual rates emphasize the importance of understanding operational limitations and external factors affecting machinery performance. Factors such as soil type, moisture content, and operator skill can significantly influence how effectively machinery can operate in the field.

Agricultural Machinery Cost Management

Effective management of machinery costs helps optimize profitability, improve efficiency, and make informed decisions regarding machinery investments. It requires a comprehensive approach that considers various factors such as equipment selection, maintenance, operator training, technology adoption, and financial planning. By applying these strategies and consistently assessing the management practices of factory machinery, we can effectively reduce costs and enhance overall operational efficiency at the Arjo Diddessa sugar factory. The study analyzed various cost components of agricultural machinery, including depreciation, repair and maintenance costs and fuel, oil costs, operator costs, and spare part costs.

Depreciation

Fig. 4 illustrates the calculated depreciation costs (Birr) of tractors at the Arjo Diddessa sugar factory, utilizing the declining balance method. The figure reveals a clear trend in how the value of each tractor decreases over time, represented by a polynomial regression curve for each model: YTO 180, New H.TM 7020, and YTO 130. The YTO 180 tractor shows the highest depreciation costs, indicating that older machinery tends to lose value more rapidly compared to newer models. The New H.TM 7020 and YTO 130 tractors exhibit lower depreciation rates, reflecting their relatively recent acquisition and better maintenance practices. The second-order polynomial functions used to analyze the relationship between depreciation cost and service life demonstrate a strong correlation, as indicated by high R^2 values (0.9993 for both New H.TM 7020 and YTO 130). This suggests that the declining balance method effectively captures the depreciation behavior of these tractors.

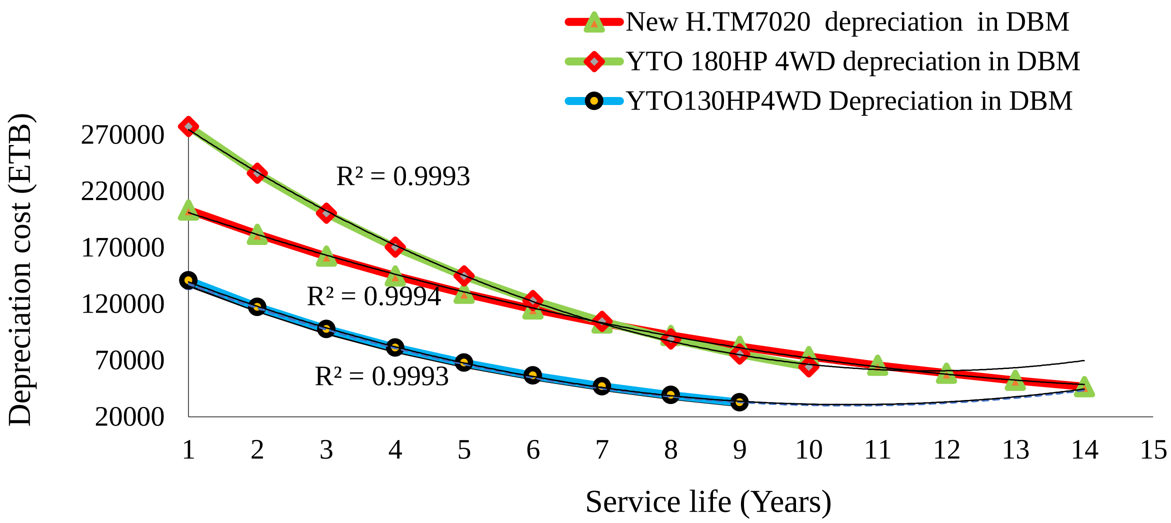

Fig. 4. Calculated Declining Balance Method (DBM) depreciation cost (Birr) of tractors

The gradual curve in the figure signifies that as the service life increases, the depreciation cost accumulates consistently, albeit at a decreasing rate. The findings also highlight the necessity for regular maintenance to prolong equipment lifespan and mitigate steep depreciation rates.

Repair and Maintenance Costs

Repair and maintenance costs play a major role in total operating costs. Newly acquired agricultural machinery begins to deteriorate from the use of machines. Especially in the study area, the environment was extremely harsh. Since tillage activities begin in the dry season, there is a lot of dust that wears out the engine and its connected parts. Machine systems and implement mechanisms had frequently failed in the farm area. Daily maintenance and a little lubrication were necessary. Failures of machine mechanisms during the peak season of the year raise the cost of downtime. Effective repair and maintenance activities are essential to reducing the cost of downtime during the peak times of the year. The repair and maintenance costs were a significant portion of the total operational costs, ranging from 25-30% across the study period.

Fuel and Oil Costs

Fig. 5 illustrates the annual farm machinery operation costs from 2016/17 to 2021/22 at the Arjo Diddessa sugar factory, highlighting significant fluctuations in various cost components over the years. Repair and maintenance costs peaked in 2020/21, suggesting an increase in maintenance needs or unexpected repairs during that period, before experiencing a slight decrease in 2021/22.

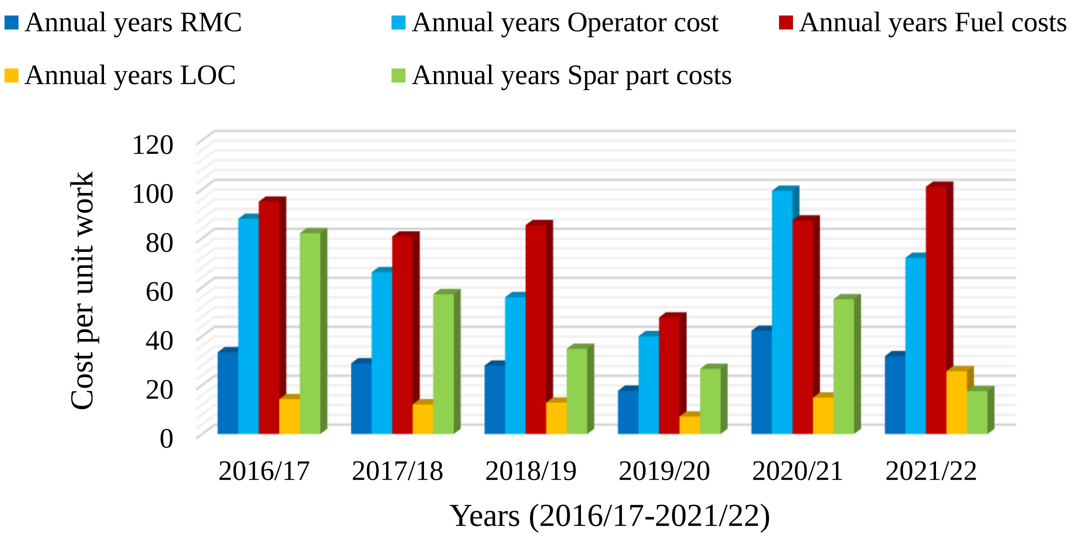

Fig. 5. Summary of annual (2016/17-2012/22) farm machinery operation costs

Operator costs show a decreasing trend from 2016/17 to 2019/20, followed by an increase in 2020/21, and then a decline again in 2021/22. These fluctuations could reflect changes in workforce size, improvements in labor efficiency, or adjustments in wage rates throughout the analyzed period. Fuel costs exhibited a consistent upward trend, increasing from 2019/20 to 2020/21 and continuing to rise in 2021/22, which may indicate rising fuel prices or increased consumption due to higher operational demands. Repair and Maintenance Costs (RMC) peaked in the fiscal year 2020/21, indicating an increase in either the frequency of failures or more intensive use of machinery, resulting in increased maintenance requirements. A slight decrease in 2021/22 may indicate improved maintenance procedures or less equipment usage. The data show a downward trend in lubricant and oil prices (LOC) from 2016/17 to 2019/20, followed by an increase in 2020/21, most likely due to increased usage, then another reduction in 2021/22. Spare part costs varied significantly over the years, with the lowest recorded cost in 2021/22 and the highest in 2016/17; this variation may be attributed to changing maintenance needs or the frequency of repairs.

Overall, total operational costs displayed fluctuations as well, peaking in 2021/22 and reaching their lowest point in 2019/20. This variation is influenced by the combined effects of repair and maintenance costs, operator costs, fuel expenses, lubricant costs, and spare part expenditures. Notably, fuel and oil costs accounted for approximately 30-35% of total operational expenses during the study period, underscoring their significant impact on overall machinery operation costs. In general, Fig. 5 provides critical insights into how different cost components contribute to the financial performance of farm machinery operations at the Arjo Diddessa sugar factory over time. As shown in Table 2, the optimization model significantly impacted reducing total operational costs, achieving a reduction of up to 10.60% during the 2021-22 period. The sensitivity analysis shows that the total operation costs for the constraint in the 2020/21 year have an allowable increase of $2.80E^{+06}$ and an allowable decrease of $9.19E^{+06}$. After optimization, the total operating costs decrease, leading to an improvement of 3.93%. The overall operation expenses for the constraint in the 2021/22 year have an allowable increase of $3.66E^{+06}$ and an allowable decrease of $2.72E^{+07}$. After optimization, the total operation cost value decreases significantly, resulting in a considerable improvement of 10.60%. The optimization model reduced the total operational costs by up to 10.60% in 2021-22 compared to the pre-optimization costs. The statistical analysis of the data using paired t-tests indicated that optimizing farm machinery significantly reduced the operational costs of the Arjo Diddessa sugar factory ($p < 0.05$) (Table 3). Tests of the model verification and analysis on a statistical basis in the case of Arjo Diddessa sugar factory reveal the opportunity to improve the control expenses, operational costs of farm machinery, and machinery distribution efficiency in the sugar factory.

Table 2- Total operational costs 2016/17-2012/22 before and after optimization

Year	Right hand side (RHS)	Allowable increase	Allowable decrease	Before optimization	After optimization	Difference	Improvement (%)
2016/17	3.02E+08	2.05E+05	1.80E+06	3.02E+08	3.00E+08	2.00E+06	0.66
2017/18	2.44E+08	5.16E+06	2.64E+05	2.50E+08	2.44E+08	5.41E+06	2.17
2018/19	2.16E+08	5.18E+06	6.13E+06	2.22E+08	2.10E+08	1.17E+07	5.28
2019/20	1.39E+08	3.03E+04	1.15E+06	1.39E+08	1.37E+08	1.18E+06	0.85
2020/21	3.02E+08	2.80E+06	9.19E+06	3.05E+08	2.93E+08	1.20E+07	3.93
2021/22	3.07E+08	3.66E+06	2.72E+07	3.10E+08	2.77E+08	3.29E+07	10.60

The sensitivity analysis indicates that the total operational costs for the constraints in the 2020/21 fiscal year have an allowable increase of 2.80 million Birr and an allowable decrease of 9.19 million Birr. Following optimization, the total operating costs decreased, resulting in an improvement of 3.93%. For the 2021/22 fiscal year, the overall operational costs for the constraints show an allowable increase of 3.66 million Birr and an allowable decrease of 27.2 million Birr. After optimization, there was a significant reduction in total operational costs, leading to a substantial improvement of 10.60%. The optimization model effectively reduced total operational costs, including both fixed and variable expenses, by as much as 8.92% in 2018-19 compared to pre-optimization figures. Statistical analysis using paired t-tests confirmed that optimizing farm machinery significantly minimized operational costs at the Arjo Diddessa sugar factory ($p < 0.05$) (Table 3). Furthermore, model verification and statistical analysis reveal opportunities to enhance control over expenses, improve operational costs associated with farm machinery, and increase machinery distribution efficiency within the sugar factory.

Table 3- T-test analysis for all total operational costs before and after optimization

Source	Paired Difference					t	Df	Sig.(p-value)
				95% Confidence Interval of the difference				
	Mean	Std. D	Std. EM	Lower	Upper			
Paired before- after	2.55E+08	6.70E+07	2.72E+07	-1.45E+06	2.32E+07	2.2673	5	0.0727

The sensitivity analysis provides critical insights into how operational costs can fluctuate based on varying constraints, highlighting the importance of understanding both allowable increases and decreases in cost components. For example, the substantial allowable decrease of 9.19 million Birr in 2020/21 suggests that there was considerable room for reducing costs without compromising operational effectiveness, indicating potential inefficiencies that could be targeted for improvement. The results from the optimization model demonstrate a clear trend toward cost reduction across multiple years, with a notable improvement of 10.60% in 2021/22.

Conclusion

The study at Arjo Diddessa sugar factory identified significant inefficiencies in machinery management, with only 37% of equipment operational and 49% requiring maintenance, leading to delays, higher costs, and reduced productivity. A 35.33% discrepancy in work rates highlighted the impact of external factors like operator expertise and field conditions. Optimization measures achieved cost savings of up to 10.60% in 2021/22, emphasizing the importance of maintenance systems, staff training, and strategic machinery replacement. Cost analysis revealed repair, maintenance, fuel, and oil as major expense drivers, underscoring the need for effective cost management strategies. Future research should focus on exploring innovative strategies to optimize energy consumption in agricultural machinery operations. This could include integrating renewable energy sources, such as solar-powered systems, and developing energy-efficient machinery designs. Additionally, studies on advanced data analytics for predictive maintenance and real-time monitoring could significantly enhance operational efficiency while reducing environmental impact. Such research would contribute to more sustainable and cost-effective management practices in the sugar production industry.

Conflict of Interest Statement

The authors declare no potential conflict of interest.

Authors Contribution

Siraj K. Busse: worked on the idea and technique, helped with manuscript preparation, and was substantially involved in the review and editing processes, guaranteeing the final document's quality. He also supervised the study process and guided its general direction.

Tefera K. Hurisa: managed the research's concept, methodology, and software development, in addition to managing data curation and performing investigations. He was instrumental in developing the project's resources and authoring the initial draft.

Esmael A. Esleman: concentrated on writing and revising the article for clarity and coherence, as well as overseeing the research to ensure its quality and rigor, improving the study's methodology as necessary.

References

1. Abbasi, R., Martinez, P., & Ahmad, R. (2022). The digitization of agricultural industry– a systematic literature review on agriculture 4.0. *Smart Agricultural Technology*, *2*(February), 100042. https://doi.org/10.1016/j.atech.2022.100042
2. Ambo, Y. (2024). Assessment of Maintenance Activities and Strategies for Tractor and Operator Care in Gurage Zone, Wolkite Town, Ethiopia. *Engineering Science*, *9*(2), 39-46. https://doi.org/10.11648/j.es.20240902.12
3. Ashine, E. T., Tilahun Ashine, E., Yesuf, M. B., & Bokke, A. S. (2022). Estimation and Mapping Spatiotemporal Variability of Crop Water Requirement for Sugarcane in Arjo Dedessa Sugar Factory and its Surrounding. *Journal of Remote Sensing and GIS*, *11*(5), 1000232. https://doi.org/10.35248/2469-4134.22.11.232
4. Ayele Zikargie, Y., & Cochrane, L. (2024). From developmentalism to the homegrown economy of Ethiopia: The narratives and the reality. *Heliyon*, *10*(15), e35021. https://doi.org/10.1016/j.heliyon.2024.e35021
5. Bhamare, D. M. A. (2023). Optimizing Crop Selection and Production Planning in Agriculture: Applications of Linear Programming for Profit Maximization and Sustainability. *International Journal of Research Publication and Reviews*, *4*(6), 3281-3287. https://doi.org/10.55248/gengpi.4.623.46630
6. Boninsenha, I., Mantovani, E. C., Costa, M. H., & da Silva Júnior, A. G. (2022). A Linear Programming Model for Operational Optimization of Agricultural Activity Considering a Hydroclimatic Forecast—Case Studies for Western Bahia, Brazil. *Water (Switzerland)*, *14*(22).

https://doi.org/10.3390/w14223625

7. Diez de Bonilla-Jiménez, O. I., Chávez-Mejía, A. C., Navarro-González, M. I., Ruiz-Velázquez, I. E., & Molina-Valencia, U. (2024). Optimization of the Disinfection Process in Potabilization Systems in Cuenca Alto Atoyac, Mexico. *Water (Switzerland)*, *16*(23). https://doi.org/10.3390/w16233451
8. Etikan, I., & Babatope, O. (2019). A basic approach in sampling methodology and sample size calculation. *MedLife Clinics*, *1*, 1006.
9. Fahmida, M., Mursalin, M. S., Huda, M. N., Shah, M. F., Hossain, M. J., & Haque, M. J. (2024). Design, fabrication and performance evaluation of a rotary power weeder for maize cultivation. *Agricultural Engineering International: CIGR Journal*, *26*(3), 71-78.
10. Firoozi, A. A., Tshambane, M., Firoozi, A. A., & Sheikh, S. M. (2024). Strategic load management: Enhancing eco-efficiency in mining operations through automated technologies. *Results in Engineering*, *24*(September). https://doi.org/10.1016/j.rineng.2024.102890
11. Gebeyehu, A. K., & Abbink, J. (2022). Land, sugar and pastoralism in Ethiopia: Comparing the impact of the Omo-Kuraz sugar projects on local livelihoods and food (in) security in the lower Omo Valley. *Pastoralism*, *12*(1). https://doi.org/10.1186/s13570-022-00242-8
12. Gebreeyessus, G. D., Mekonnen, A., Chebude, Y., & Alemayehu, E. (2021). Quantitative characterization and environmental techno-legal issues on products and byproducts of sugar and ethanol industries in Ethiopia. *Renewable and Sustainable Energy Reviews*, *145*(April), 111168. https://doi.org/10.1016/j.rser.2021.111168
13. Jupiara, B., Schardong, F., Ribeiro, R. P., Guilherme, N., Pinto, M., & Fagundes, P. D. M. (2024). Optimization in Agricultural Management : Exploring Linear Programming for Rural Properties. *IOSR Journal of Business and Management*, *26*(4), 57-65. https://doi.org/10.9790/487X-2604015765
14. Kalwar, M. A., Khan, M. A., Shahzad, M. F., Wadho, M. H., & Marri, H. B. (2022). Development of linear programming model for optimization of product mix and maximization of profit: case of leather industry. *Journal of Applied Research in Technology & Engineering*, *3*(1), 67-78. https://doi.org/10.4995/jarte.2022.16391
15. Kolhe, K. P., Lemi, D. G., & Busse, S. K. (2024). Studies of tractor maintenance and replacement strategies of Wonji Shoa Factory, Ethiopia. *Journal of Agricultural Engineering*, *55*(1). https://doi.org/10.4081/jae.2024.1552
16. Nunes, P., Santos, J., & Rocha, E. (2023). Challenges in predictive maintenance– A review. *CIRP Journal of Manufacturing Science and Technology*, *40*, 53-67. https://doi.org/10.1016/j.cirpj.2022.11.004
17. Oladejo, N. K., Abolarinwa, A., & Salawu, S. O. (2020). Linear Programming and Its Application Techniques in Optimizing Portfolio Selection of a Firm. *Journal of Applied Mathematics*, *2020*. https://doi.org/10.1155/2020/8817909
18. Papageorgiou, A. (2015). Agricultural Equipment in Greece: Farm Machinery Management in the Era of Economic Crisis. *Agriculture and Agricultural Science Procedia*, *7*, 198-202. https://doi.org/10.1016/j.aaspro.2015.12.017
19. Pejić Bach, M., Topalović, A., Krstić, Ž., & Ivec, A. (2023). Predictive Maintenance in Industry 4.0 for the SMEs: A Decision Support System Case Study Using Open-Source Software. *Designs*, *7*(4). https://doi.org/10.3390/designs7040098
20. Rahman, M. M., Ali, M. R., Oliver, M. M. H., Hanif, M. A., Uddin, M. Z., Tamim-Ul-Hasan, Saha, K. K., Islam, M. H., & Moniruzzaman, M. (2021). Farm mechanization in Bangladesh: A review of the status, roles, policy, and potentials. *Journal of Agriculture and Food Research*, *6*, 100225. https://doi.org/10.1016/j.jafr.2021.100225
21. Salawu, E. Y., Awoyemi, O. O., Akerekan, O. E., Afolalu, S. A., Kayode, J. F., Ongbali, S. O., Airewa, I., & Edun, B. M. (2023). Impact of Maintenance on Machine Reliability: A Review.

E3S Web of Conferences, *430*, 1-12. https://doi.org/10.1051/e3sconf/202343001226

22. Shaheb, M. R., Venkatesh, R., & Shearer, S. A. (2021). A Review on the Effect of Soil Compaction and its Management for Sustainable Crop Production. *Journal of Biosystems Engineering*, *46*(4), 417-439. https://doi.org/10.1007/s42853-021-00117-7
23. Sun, J., Zhang, Y., Chen, H., & Qiao, J. (2023). Optimization Model and Application for Agricultural Machinery Systems Based on Timeliness Losses of Multiple Operations. *Agriculture (Switzerland)*, *13*(10), 1-19. https://doi.org/10.3390/agriculture13101969
24. Yaseen, M. U., Ahmad, S., Ahmad, M., Long, J. M., Raza, H. A., Iftekhar, H., Ameer, S., & Ogunbiyi, D. (2024). A Multi-Function Novel Crop Seeder for the Management of Residues and Mechanized Sowing of Wheat in a Single Path. *AgriEngineering*, *6*(3), 2445-2469. https://doi.org/10.3390/agriengineering6030143
25. Zhang, H., Yang, Z., Wang, Y., & Twumasi, M. A. (2023). Impact of Agricultural Mechanization Level on Farmers ' Health Status in Western China : Analysis Based on CHARLS Data. *International Journal of Environmental Research and Public Health*.
26. Zhang, Q., Zhao, J., Yang, X., Wang, L., Su, G., Liu, X., Shan, C., Rahim, O., Yang, B., & Liao, J. (2024). Design and Testing of an Offset Straw-Returning Machine for Green Manures in Orchards. *Agriculture (Switzerland)*, *14*(11). https://doi.org/10.3390/agriculture14111932
27. Zikargie, Y. A., Wisborg, P., & Cochrane, L. (2022). State-led modernization of the Ethiopian sugar industry: questions of power and agency in lowland transformation. *Journal of Eastern African Studies*, *16*(3), 434-454. https://doi.org/10.1080/17531055.2023.2166449
28. Zikargie, Y. A., Wisborg, P., & Cochrane, L. (2023). State-led modernization of the Ethiopian sugar industry: questions of power and agency in lowland transformation. *Journal of Eastern African Studies*, *16*(3), 434-454. https://doi.org/10.1080/17531055.2023.2166449

ارزیابی و بهینه‌سازی هزینه‌های سیستم مدیریت ماشین‌آلات کشاورزی در کارخانه قند آرجو دیدسا

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چکیده

نظارت کارآمد بر ماشین های کشاورزی در کارخانه‌های قند برای حفظ کیفیت محصول، مدیریت هزینه‌های عملیاتی و بهبود بهره‌وری بسیار مهم است. صنعت قند اتیوپی برای اقتصاد این کشور حیاتی است؛ با این حال، مشکلات مربوط به مدیریت ماشین ها می‌تواند منجر به هزینه‌های نگهداری بالاتر و بهره‌وری عملیاتی پایین شوند. هدف این مطالعه، ارزیابی سیستم مدیریت ماشین های کشاورزی در کارخانه قند آرجو دیدسا و بهینه‌سازی هزینه‌های عملیاتی است. بین سال‌های ۲۰۱۶ تا ۲۰۲۲، داده‌ها از طریق نظرسنجی، مصاحبه و مشاهدات عینی جمع‌آوری شدند. برای بهبود هزینه‌های جاری ماشین ها، یک مدل خطی با استفاده از نرم‌افزار LINDO مورد مطالعه قرار گرفت. یافته‌ها نشان می‌دهند که از بین ماشین های غیرفعال، ۴۹ ٪ نیاز به تعمیر جزئی دارند و ۱۴ ٪ غیرقابل تعمیر هستند و باید به‌طور کامل از چرخه حذف شوند. نرخ کار پیش‌بینی‌شده ۳۵/۳۳ ٪ از نرخ واقعی فراتر رفت. از بین وظایف، ریشه‌کنی با ۵/۷۳ ٪ کمترین اختلاف را با نرخ کار واقعی داشت، در حالی که کشت ردیفی با ۶۷/۲۱ ٪ بیشترین اختلاف را با نرخ واقعی نشان داد. هزینه‌های اولیه تعمیر کمینه بودند، اما با افزایش سن تجهیزات، هزینه‌های تعمیر نیز افزایش یافتند. مدل بهینه‌سازی در سال زراعی ۲۰۲۲-۲۰۲۱ منجر به کاهش ۱۰/۶۰ درصدی هزینه‌های عملیاتی شد که اهمیت تخمین دقیق نرخ کار واقعی ماشین‌آلات و تحلیل عملکرد را برای افزایش بهره‌وری برجسته می‌کند. در این مطالعه، ناکارآمدی‌های اساسی در مدیریت ماشین‌آلات شناسایی شدند و بر نیاز به سیستم‌های تعمیر و نگهداری قوی و برنامه استراتژیک جایگزینی تجهیزات فرسوده تاکید می‌شود. بهینه‌سازی بهره‌وری عملیاتی برای بهبود بهره‌وری و کاهش هزینه‌ها در فرآیند تولید قند ضروری است.

واژه‌های کلیدی: بهره‌وری عملیاتی، سیستم مدیریت ماشین‌آلات، ظرفیت مزرعه‌ای ادوات، عملکرد تعمیر و نگهداری

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