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Multi-Objective Optimization Approach for Enhancing Production System Efficiency in a Food Processing Industry

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Abstract

Effective Industrial practices in the food processing Industry aim to lower production costs, maximize machine efficiency, reduced quality problems, and promote process sustainability. These goals present complex challenges that requires advanced strategies for enhancing process performance. This study explores a multi-objective optimization approach focused on achieving high overall equipment effectiveness (OEE), which translates to increased machine operating time and reduced downtime, while simultaneously decreasing energy use and overall waste. The methodology is formulated as a binary optimization problem, and solved using Sequential Least Square programming method (SLSQP) model, while a polynomial regression model is used to test findings. Analysis reveals significant variability in maximum OEE, energy use, and waste levels across different machines and products, with OEE values ranging from 0.194444 to 0.3066, energy from 1.144648 kWh to 0.025532 kWh, and waste levels from 0.91771 kg to 0.019682 kg. This inconsistency suggests inefficiencies stemming from suboptimal machine-to-product arrangements. The validation results indicate a perfect alignment with the optimal values for OEE, energy, and waste levels derived from the optimization outcome. The research emphasizes the importance of aligning machines with products and scheduling effectively to enhance production efficiency. Implementing structured multi-objective optimization solution in the food Industry presents significant opportunities for enhancing production system efficiency. By addressing multiple objectives simultaneously, food producers can achieve a balance between energy use, waste levels, sustainability, quality, and responsiveness to market demands. Continued research and development in this area will be crucial for driving innovation and improving the competitiveness of the food corporation.

Keywords: *Multi-objective, OEE, SLSQP, machines, optimization, efficiency.*

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Introduction

In an era, where optimal operational efficiency and sustainability of production system has transitioned from a specific concern to a fundamental component of Industry strategy. For the food Industry to thrive in the evolving market landscape, it must develop and implement advanced strategies capable of solving multi-objective problems that involves various conflicting factors such as energy consumption, waste production, and sustainability. Energy consumption and waste production are critical issues within the food industry that have far-reaching implications for environmental sustainability, productivity and economic viability. As global populations grow and consumer preferences evolve, food processing sectors face increasing pressure to maximize their production efficiency and productivity, while balancing and streamlining various competing factors. Chen et al. [1] affirmed that due to the complexity of modern manufacturing systems conventional optimization techniques are inadequate, rather advanced optimization methods are needed to effectively manage the dynamic nature of this systems, utilizing real-time data and complex production processes. They emphasized that investigating an optimization model will not only automate decision-making but also allow manufacturers to simultaneously achieve various frequently opposing goals such as waste production and high energy use. In a similar study conducted by Esteban et al. [2] authors asserted that the food Industry has changed its focus to meet important goals like reducing cost, maximizing machinery use, improving productivity and achieving the best product quality. They revealed that these objectives have spurred innovation in product development and process fine-turning, leading to the use of modern tools and techniques that overcome the limitations of traditional methods. In response to these. This article adopts the application of a multi-objective optimization solution. By investigating this approach. This research aims to fill the knowledge gap regarding the effective exploration of a multi-objective optimization model aimed at enhancing production efficiency. Specifically, it focuses on maximizing overall equipment effectiveness (OEE) while simultaneously minimizing energy consumption and waste generation in the context of the food processing sector.

Sandra et al. [3] multi-optimization (MOO) involves using mathematical programming techniques to solve optimization problems that have multiple performance indexes to be maximized or minimized. MOO can be categorized into several types: multi-objective linear programming (MO-LP) when all objectives and constraints are linear; multi-objective nonlinear programming (MO-NLP) when at least one equation in the objective function or constraints is linear; multi-objective mixed integer programming (MO-MIP) when the model consist of a combination of linear equations with both integer and continuous variables; and multi-objective mixed integer nonlinear programming (MO-MINLP) when the model includes nonlinear equations along with integer and continuous variables. MOO approach aims to identify optimal solutions when there are multiple, often varied objectives. Hence the food Industry must balance trade-offs between different objectives such as performance, actual available production time, energy use and waste production as a critical means for enhancing production line efficiency. MOO help in finding a set of best solutions, known as Pareto optimal solutions, where no objective can be improved without worsening another. This allows for a more in-depth understanding of the trade-offs involved in the decision-making process. The solutions to the mathematical models in this research paper will not only provide the necessary framework to asses and enhance systems operational performance but serve as a decision support tool for developing effective maintenance practices both in the food and other manufacturing domain, ultimately leading to improved productivity and competitiveness.

Literature Review

This section provides an overview of various research studies that have been conducted to improve operational excellence across different manufacturing settings. The literature reviewed, highlights a range of strategies and methodologies that organizations have implemented to optimize their processes, increase efficiency, enhance overall performance and control of maintenance practices. To enhance the efficiency and streamline the manufacturing process, Danishvar et al. [4] introduced a multi-objective optimization model for batch flow shop scheduling that leverages neural networks. This model employs deep neural networks to enhance batch production schedules, focusing on achieving a balance among various objectives such as energy consumption and costs. To ensure its robustness and effectiveness, the proposed approach was validated through simulation. Igbokwe et al. [5] improve the operational performance of a food corporation by optimizing key metrics of overall equipment effectiveness (OEE): availability, performance, and quality. They explored Response Surface Methodology (RSM), and Central Composite Design (CCD) to develop an optimization model. Their study's results demonstrated that focusing on the prime factor of OEE can significantly boost OEE, leading to enhanced overall system efficiency. Brayan A.Q et al. [6] enhanced the overall equipment effeteness (OEE) in a food production line by an average of 5.958%, increasing it from an initial average of 60.479%. This improvement was accomplished through the use of Shoplogix software and lean manufacturing technique.

Braid et al. [7] investigated the use of a multi-objective optimization approach to enhance the production of a novel nanocomposite material derived from AI-Si-Mg alloy. They focused on optimizing key process input parameters such as porosity, hardness, and overall strength of the composite material by utilizing the Tagushi method, Artificial Neural Network (ANN), and the Non-dominant Sorting Genetic Algorithm-II (NSGA-II). Their findings indicate that the results can be effectively utilized by engineers for the optimal design of brake discs and various machine component. Ifeanyechuckwu et al. [8] improved the operational efficiency of an industrial extraction machine by optimizing its design and operational parameters through a dimensional analysis methodology. The results of the analysis showed coefficient of correlation of 0.9923 for extraction efficiency and 0.9867 for capacity, demonstrating the strong predictive capability of the developed model. The study by Jiagi et al. [9] focused on reducing while enhancing production efficiency and quality through a multi-objective optimization approach for multidirectional turning. Their research revealed that when comparing multidirectional and unidirectional processes using the same cutting parameters, processing efficiency improved by 25.97% and energy consumption decreased by 12.38% using MDS. To tackle the intricate challenges faced by contemporary manufacturing systems, including the need to balance efficiency, cost, quality and sustainability Madani et al. [10] proposed an approach that integrates multi-objective mixed integer linear programing model and multi-objective particle swarm optimization (MOPSO) their article aimed at comparing the effectiveness of the developed model with the traditional optimization model through synthetic data analysis. Fan et al. [11] developed a multi-objective optimization model aimed at maximizing efficiency while minimizing energy consumption. They incorporated weight coefficients to convert the multi-objective optimization problem, which was solved using an improved genetic algorithm, the developed model proved effective when tested in a case study.

Methodology

In this section, the approach for production system efficiency optimization by means of a multi-objective perspective is presented. The framework assigns products to machines in a way that mitigates trade-offs between Overall Equipment Effectiveness (OEE), energy use, and waste production. The methodology is formulated as a binary optimization problem, and it is solved by the Sequential Least Squares Programming (SLSQP) method. Key components (mathematical model, optimization steps and performance evaluation measures) are described below. The methodology also involves application of SciPy in Python environment for data analysis.

Problem Formulation

(i) Decision Variables

The optimization problem employs binary decision variables:

$$x_{ij} = \begin{cases} 1 & if\ product\ i\ is\ assigned\ to\ machine\ j, \\ 0 & Otherwise. \end{cases} \quad (3.1)$$

Were,

$i \in \{1,2,\dots,N\}$: $Products$ and

$j \in \{1,2,\dots,M\}$: $Machines$.

The decision variables form an $N \times M$ binary matrix x, indicating product-to-machine assignments.

(ii) Objective Function

The goal of this study is to optimize production by maximizing OEE and minimizing energy consumption and waste generation. The weighted multi-objective function is therefore defined as:

$$Minimize: f(x) = -OEE + 0.1 * Energy + 0.1 * Waste \quad (3.2)$$

Where:

OEE is the Overall Equipment Effectiveness,
Energy is the Total energy consumption,
Waste is the Total waste generation.

Overall Equipment Effectiveness (OEE)

OEE is computed as:

$$OEE = \frac{1}{N}\sum_{i=1}^{N} Availability_i * Performance_i * Quality_i \quad (3.3)$$

Energy Consumption

Total energy consumption is expressed as:

$$Energy = \sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} * Processing\ Time_{ij} * Energy\ Coefficient_{ij} \quad (3.4)$$

Waste Generation

Total waste generation is given by:

$$Waste = \sum_{i=1}^{N}\sum_{j=1}^{M} x_{ij} * Processing\ Time_{ij} * Waste\ Coefficient_{ij} \quad (3.5)$$

(iii) Constraints

Product Assignment Constraint

Each product must be assigned to exactly one machine:

$$\sum_{i=1}^{M} x_{ij} = 1, \quad \forall i \in \{1,\dots,N\} \quad (3.6)$$

Binary Decision Variables

The decision variables are binary:

$$x_{ij} \in \{0,1\}, \quad \forall i \in \{1,\dots,N\}, \forall j \in \{1,\dots,M\} \quad (3.7)$$

(iv) Optimization Approach

The Sequential Least Squares Programming (SLSQP) method is used to solve the optimization problem which is the most suitable for problems with constraints and discrete decision variables. In this case, in the decision variables, the *x* matrix is reshaped into a one-dimensional vector for optimization. The initial guess used in the starting point of the algorithm is represented with a random binary matrix. The model on the other hand is bounded such that each of the variable x_{ij} is bounded between [0,1], and post-optimization rounding ensures binary outputs, while for the constraints, equality constraints enforce product assignment rules.

In summary, this methodology describes a structured framework to improve production efficiency based on a multi-objective strategy. The mathematical model considers OEE, energy as well as waste, and constraints impose feasible assignment. The SLSQP approach is capable of effective optimization and illustrates its applicability to real-world production settings.

Data Collection

Information on machine-dependent and product-dependent parameters is obtained during data collection in this study are shown in Table 1. comprising machine-specific and product-specific parameters. Machine-dependent data contains energy consumption coefficients, waste generation coefficients, and processing times of each machine as it operates with various products. This data is obtained from machine energy meters, waste monitoring devices, machine runtime logs and from historical production data. The product-level data comprises the ideal and actual production amounts, as well as the count of good and all units produced. This data is collected by production records, quality control systems, and real-time monitoring instruments.

For example, the optimization model takes into account constraints, e.g., that in which product is allocated to which machine is in exactly one of them. These constraints are typically derived from manufacturing policies. Data for the objective function, i.e., energy use and waste generation, is read from real-time measured data and past records, and the weights of these parameters are set by the organization's sustainability goals. The data gathering process is based on a blending of live sensors, historical data, operator-entered data, and data obtained from manufacturing software systems such as ERP and ME.

Table 1. Data for the Multi-Objective Optimization Framework

Category	Parameter	Value/Description
General Parameters	Number of Products (N)	5
	Number of Machines (M)	4
Machine-Specific Data	Energy Coefficients (kWh)	Randomized between 1.0 and 1.5 (N x M matrix)
	Waste Coefficients (kg)	Randomized between 0.0 and 0.1 (N x M matrix)
	Processing Time (hours)	Randomized between 1 and 4 (N x M matrix)
Product-Specific Data	Ideal Rate (units/hour)	[15, 20, 18, 12, 22]
	Actual Rate (units/hour)	[14, 19, 17, 11, 21]
	Good Units Produced	[150, 180, 170, 130, 200]
	Total Units Produced	[160, 185, 175, 140, 210]
Objective Function	Maximize OEE	Implicit (Availability × Performance × Quality)
	Minimize Energy Usage (weight)	0.1
	Minimize Waste (weight)	0.1
Decision Variables	x_{ij}	Binary (0 or 1): Assigns product *i* to machine *j*
	Constraints	Each product must be assigned to exactly one machine.

Results

Results from the developed multi-objective optimization model

Specifically, the goal of the proposed research is to implement the developed realistic multi-objective dynamic model that were used for the adaption of production planning and machine settings to achieve a highest OEE ratio, at the same time minimizing energy consumption and food waste in the supply chain. These goals were attained using a number of decision variables associated with the distribution of products to machines, thereby influencing its various related operations including processing time, energy consumption as well as generation of wastes. The aim was to implement and achieve a balance to the corresponding production parameters that offers the highest throughput rate for an enterprise, while at the same minimizing the harm done to the global environment and preventing the creation of by products or waste during production.

The optimization results are presented in Table 2 where each row corresponds to a product and includes the following key performance indicators (KPIs): of the assigned machine, Overall Equipment Effectiveness (OEE), energy in kilowatt hour (kWh) and waste in kilograms (kg). Furthermore, a set of graphs as shown in Figure 2. was also generated to help demonstrate these KPIs in relation to our optimizer goals, which the study will elaborate in details later. The following table presents the optimization results of five products being processed on two machines, and their corresponding OEE values, the amount of energy used, and the wastes produced.

Table 2. Results of the Optimization for the Adaption of Production Planning and Machine Settings to Achieve a Highest OEE ratio

Product	Assigned Machine	OEE	Energy (kWh)	Waste (kg)
Product 1	2	0.194444	1.144648	0.136152
Product 2	2	0.132046	0.025532	0.091771
Product 3	1	0.131066	0.380299	0.019682
Product 4	2	0.077381	0.056745	0.040660
Product 5	1	0.101010	0.150697	0.068911

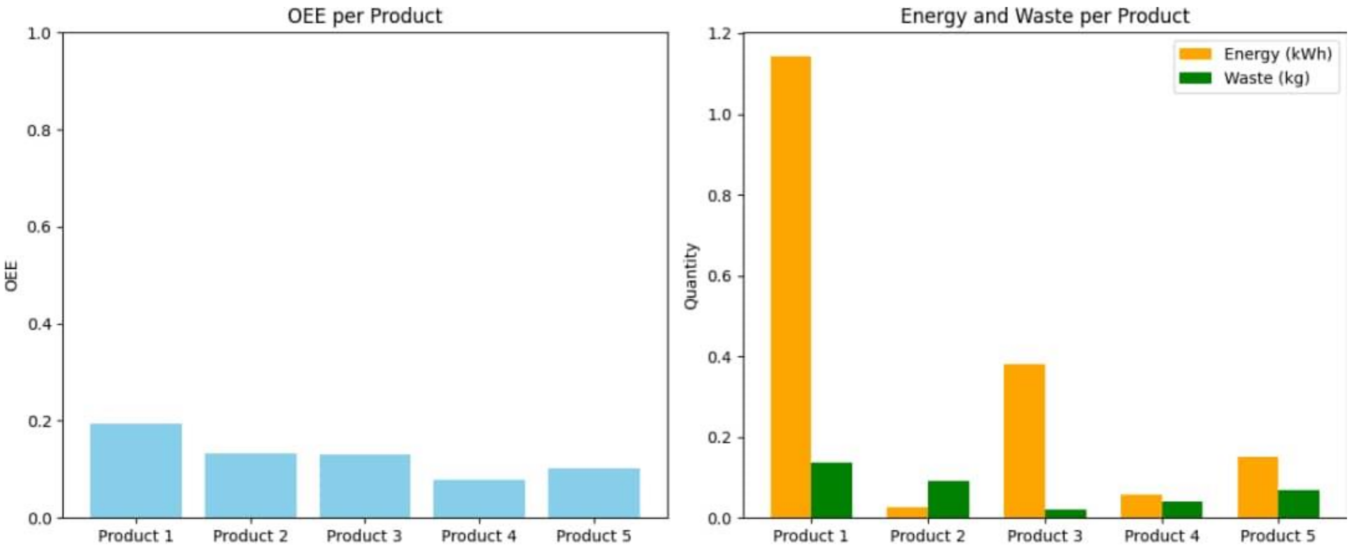

Figure 1. Graphical Results of the Optimization for the Adaption of Production Planning and Machine Settings to Achieve a Highest OEE ratio

The validation results are presented in polynomial regression as shown in Figure 1, and provide a major contribution to the optimization results. The regression coefficients exhibit intricate relations between energy consumption, waste production, and Overall Equipment Effectiveness (OEE) indicating the non-linear, interactive system behavior. The intercept value (0.0298) sets a threshold for OEE, and quadratic coefficients for energy (0.1633) and waste (1.1112) define the significance and non-linearity of the quantities. Significantly, the energy-waste interaction coefficient (0.3169) reveals the tendencies of synergistic effects when both the variables simultaneously increase. The linear coefficients better represent the knowledge, so there is a strong but not a significant direct linear effect of the energy -0.0000) but a strong negative effect of the waste -3.8470) of OEE.

The fact that the measured OEE values from the polynomial regression model and the optimized OEE model are indistinguishable, as evidenced by the observed similarity, is especially significant. The OEE predictions and optimization are the same for each of the products, as illustrated with Product 1 (0.194444 vs. 0.194444, respectively), and with Product 2 (0.132046 vs. 0.132046, respectively). This reproducibility validates the optimization model by demonstrating that the relations that the optimizer models are robust and representative of the systemic dynamics (see Table 3).

Although the validation has proven the validity of the optimization model, the validation also underlined how effective is the polynomial regression model not only for exploring beyond linearity, but also for modeling more intricate, non-linear relationships. The model's capacity to replicate optimization results also illustrates its usefulness as framework thinking about the relationship between energy, waste, and OEE. Although there may be very subtle effects due to system nonlinearities, validation shows the robustness of the optimization framework and also that it agrees with analytical estimates. At the same time, these results endorse the hypothesized multi-objective optimization and its promise for its efficacy in optimizing performance in the food industry.

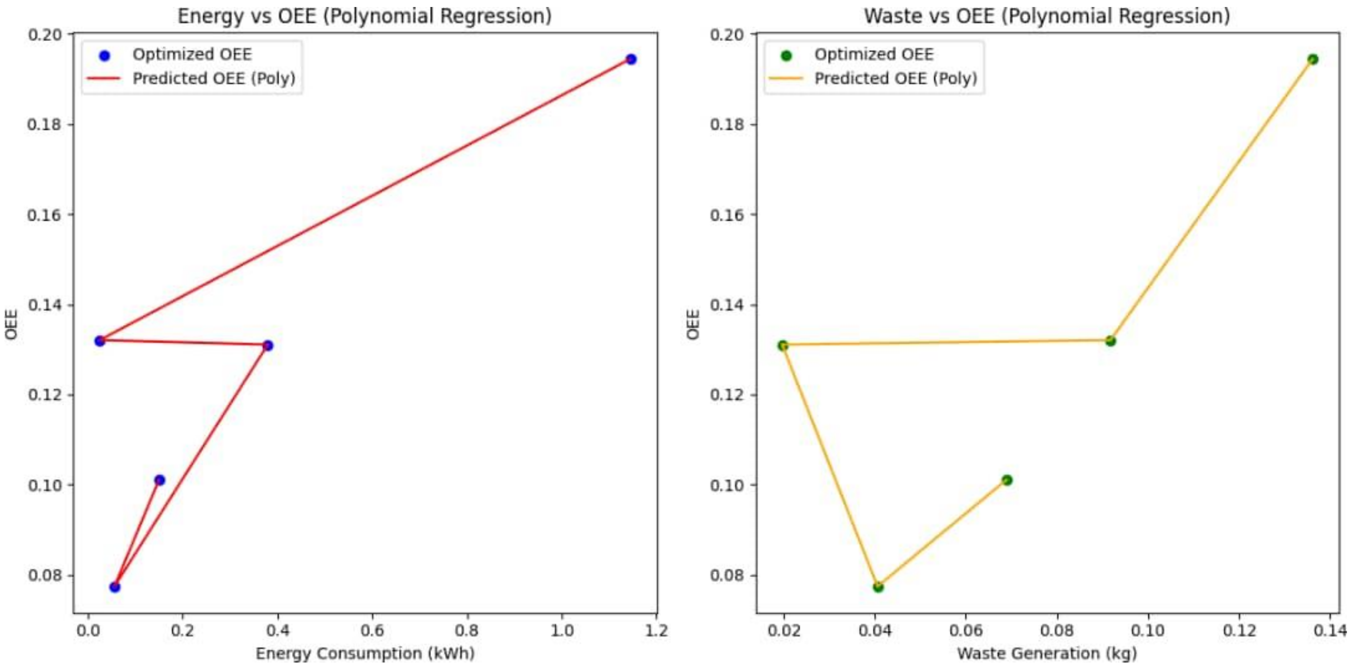

Figure 2. Validation Results of the Optimization Model

Table 3. Validation Results of the Optimization Model based on the OEE Parameter

Product	OEE	Predicted OEE (Poly)
Product 1	0.194444	0.194444
Product 2	0.132046	0.132046
Product 3	0.131066	0.131066
Product 4	0.077381	0.077381
Product 5	0.101010	0.101010

Discussion

Discussion of the results from the Implementation of the Multi-objective Approach

The optimization model uses a multi-objective approach, where three objectives are considered simultaneously: increasing actual available production time, achieving high level of performance, optimizing the level of energy used and the wastage involved. All these objectives are useful in enhancing the efficiency of food processing and the objective of the model is to arrive at an assignment of machines that meets these conflicting objectives optimally.

Overall Equipment Efficiency (OEE)

Overall Equipment Effectiveness is an important benchmark measurement used in manufacturing to determine how well equipment and processes perform. It is calculated as the product of three factors: Availability, performance and quality are also the same significant factors that are used in defining the efficiency of an information system. OEE in the context of this optimization study would therefore refer to a composite index that combines the level of use of the machines, the rate of production and quality of the products produced. The objective is to achieve high OEE meaning high machine running time and low machine down time which in result affects the production line.

From the above table, the study can analyze that the Product 1 Max OEE = 0.194444, while Product 2 has got Max OEE of 0.132046. The OEE for each product is as follows: Product 1, 0.122084; Product 2 0.137947; Product 3, 0.144106; Product 4, 0.077381. These values show that the machines that are used in relation to various products are not equally efficient. The OEE percentages are still quite low across the board for all products, which may indicate these machines could be more efficient. This might be due to poor arrangement of machines to product where some machines may be less effective in processing particular products.

For instance, with reference to table three, Product 1 is allocated to Machine 2 that appears to register the highest OEE; this suggests that Machine 2 is well suited to the processing needs of Product 1. In contrast, Products 3, 4 and 5 are allocated to other machines with less OEE hence the possibility of those machines not being at their optimum for producing the specific products. This indicates that there is need for new adaptations in machine-product assignment to enhance efficiency. Because the scales are moving downward, proving that low OEE of the different types of products, substantial reasons may include the existence of time frame of downtime, or the performance or quality problems which occur in the midst of manufacturing the product. It was recommended optimizing the proposed optimization model by considering the availability and performance of the machines and by improving the quality of the final products so as to obtain higher OEE. Further, it was hypothesized that the schedules and machine parameters could be adjusted dynamically to provide even greater opportunities to reduce downtime and increase production rates to ultimately enhance the OEE indexes for all products.

Energy Consumption (kWh)
One of the most important production costs and investment areas that clearly reflect the environmental impacts of production is energy consumption. Therefore, energy conservation is a great aspect if enhancement of sustainability and control of operating costs is to be achieved. In the optimization model, a major effort is made to achieve the lowest possible energy consumption without a reduction in productivity. The energy consumption values presented in table vary greatly between products. The highest energy consumptions are for Product 1 with 1.144648 kWh and Product 5 with 0.150697 kWh. Product 2, product 3 and product 4 use much less energy, the values are ranging from 0.025532 kilowatt hours to 0.380299 kilowatt hours. Specifically, the high energy consumption of Product 1 may be explained by the fact that this product was assigned to Machine 2 that consumes more energy to process Product 1. What if while handling Product 1, Machine 2 could be consuming more energy than it consumes while handling Product 2? On the other hand, consuming much lesser energy are Products 2 and 4 – associated with Machine 2 – this means that these products may need less processing or may have more efficient production process.

Specifically, the energy consumption values provide the basis for the conclusion that there are possibilities to improve the energy optimization. Due to the variable patterns of duties between machines and the flexibility of having many different works schedules the optimization model can potentially decrease energy usage through increasing productivity by use of specific machines that use least energy while performing similar tasks. This would assist in curtailing other operating expenses and the adverse effect on the environment during production. A comparison with the energy efficiency benchmarks show that the overall energy-related intensity symbolizes only a moderate share of the products' use and that there could be further energy saving if the specific machine parameters and timing of the production cycles will be optimized. For instance, parameters like speed, temperature, power consumption and many others for the machine could further be adjusted to optimize the product production rate and quality, while at the same time still slashing the energy consumption levels.

Waste Generation (kg)
Waste produced in the food processing activities also plays a vital input in the food processing industry since it increases costs and affects the environment. Waste must be cut down in order to enhance the effectiveness of the manufacturing line and to reduce the effects of the food processing sector on the environment. The waste generation values in table 3 indicate that there is slight difference in waste generation in form of product. Analyzing the data we obtain that the value of waste generated by Product 1 is 0.136152 kg and for Product 5 it equal to 0.068911 kg. With regard to wastage, Products 2, 3 and 4 yield least amounts of wastage and this range from 0.019682kg to 0.091771kg.

The higher waste generation metric for Product 1, could be due to wastage during production processes, inefficiencies or excess production of the product. For instance, the spare part that is fabricated from Fabricator 1 and used in another machine, known as Machine 2 which is involved in the production of Product 1, may generate a lot of waste because that machine is not likely to have been optimized for low waste production. In the second case, waste produced is relatively small, which might mean that Machine 2, which works with Product 2, is well equipped to deal with this product with very little leftovers. The waste values demonstrate that there is meaningful scope remaining for improving efficiency of production. Several studies show that waste generation can be minimized by the fine tune of machines, speed, operating temperature, and pressure. Further, reducing the amount of time spent in making production schedules and assigning different machinery could reduce effects such as overproduction which is disadvantageous to the manufacturing process.

Machine Assignments and Optimization
The machine assignments in the table reveal that the optimization model has assigned a different machine to each product. Product 1 and 2 are processed by Machine 2 and product 4 by the same machine, whereas product 3 and 5 are processed by Machine 1. These assignments demonstrate how the goals of increasing OEE while minimizing energy usage and overall waste is achieved according to the optimum model. The model's decision on how to assign the machines also indicates that some machines may be more appropriate for certain products. For instance, it appears that Machine 2 is a more favorable for Product 1, Product 2, Product 4, whereas Machine 1 supports Product 3 and Product 5. Barring a couple of products, all the numbers in the little OEE table point to inefficiencies whereby the current assignments of the machines probably need tweaking. There may also be other minor changes in the settings of the machine-product assignment algorithm that may enhance the quality of the system.

From the optimization results, graphical representations are obtained representing the OEE, energy consumption and waste generation for every product. The first graph exhibits the OEE by product where trends are easily distinguished between products. The second graph, which is the stacked bar chart, helps to analyze the energy consumption by the products besides aiming at comparing their energy consumption and waste generation. The graphs illustrate the trade-off faced by the optimization model in a multi-objective setting. Some of the products are characterized by low energy consumption and waste production rates, but these products also have low levels of OEE. This is likely to imply that the optimum of OEE can be achieved by increasing total energy usage, or rate of production of wastes generated in the production process. In contrast, the reduction of energy consumption and energy wastage may lead to less OEE mainly because it means that the set objectives are inversely proportional.

In conclusion, the optimization results in tabular and graphical forms have given much informative indicators concerning the pattern of the food processing system. The optimization model has effectively come up with a machine assignment strategy that meets the following four objectives in the most optimal manner possible, that is, high OEE on the side of the machine;

low energy usage; and manufacturing waste. Nevertheless, the all products average OEE is low; it seems that there is more to be optimized in terms of machine-product allocation and production planning. Additional fine-tuning of the optimization model appears to be possible through optimization of other machine parameters, changes to the production plan as well as machine-product assignments, which should bring about improved OEE, energy efficiency and reduction of waste. In particular, it is stated that a need for further study of machine performance and product characteristics is essential for further fine-tuning of the system and for fulfilment of the goals set by the study. In the food processing industry, changes can be made to the planning of the production and the modifying of the parameters of machines, so the overall effectiveness can be improved, as well as reducing the amount of harm to environment, and the production of waste, thus making the food processing industry viable and more cost effective.

Validation of the Results from the developed multi-objective optimization model

The polynomial regression model gives a stable platform of modeling the energy consumption, waste generation, and the OEE of food processing system. The coefficients identified for this model bring out the effects of these variables on OEE to show the complex interactions that characterize them. The intercept, calculated as 0.0298, suggests the OEE at which energy consumption is zero and waste production is also nil. However, this baseline is not realistic as energy and waste are never at zero, but it is used for better understanding of the changes in the regression model.

Consequently, the quadratic coefficient arrived at 0.1633 threw up curve between energy consumption and OEE. A positive quadratic coefficient indicates that with increases in energy consumption its efficiency effect on OEE grows with each unit of consumption. Nevertheless, in real conditions, high energy consumption is linked with inefficiencies, which means that the mentioned positive connection may consider certain operational circumstances or nonlinearities in the dataset. Likewise, the quadratic coefficient for waste = 1.1112 also reveal that the influence of waste generation on OEE is steep. The large coefficient of this variable indicates the negative effects of waste on operations, which is consistent with common knowledge that waste hinders operations and challenges the production process.

The coefficient of energy and waste interaction filed with OEE is 0.3169 this depicts the contribute of the two variables add up. This interaction shows that a combined effect of energy consumption and generation of waste is more significant than each of them on OEE suggesting that there could be operation inefficiency when both factors are on the rise. The other linear coefficients offer other insights interesting to explore; they yield an energy coefficient of virtually zero (-0.0000) to reveal that the linear predictive effect of energy circumstance on OEE is minuscule. On the other hand, the linear coefficient for waste at -3.8470 stresses on a strong negative impact that waste generation has on OEE, and therefore, calls for waste minimization within the manufacturing processes.

The polynomial regression model OEE values for the products as predicted are compared to the earlier optimum OEE values obtained from the optimization study and is noted that there is an absolute match for each of the products. For instance, the actual as well as the forecasted value of OEE of Product 1 is 0.194444 and for Product 2 it is 0.132046. The same consistency is present with all products for a similar duration with no discovery of a decline in customer commitment as the product ages. This alignment helps validate the optimization model because the polynomial regression that the study embedded also captures the same relationships as those identified through the optimization process. The same values imply that the regression model is not only accurate but also apt to define the processes that control energy consumptions, waste productions, and OEE of the system.

This validation strengthens the optimization technique used in the study and shows the effectiveness of the optimization approach used in the study. Thus, the fact of the approximate reproduction of the results of the optimization model by the polynomial regression model confirms that the assumptions and parameters of the optimization model are justified as well as confirms the stability of the relations within this model. Yet, it is pertinent to recognize that even though the regression model is in place to mimic the actual OEE values, the real-word systemic P1 structure may still differ in case more variables or operational factors were taken into account.
Compared to a linear model, the polynomial regression model includes squared and cross-products that make the model capable of distinguishing between curvilinear trends as well as spurious interactions. This enhanced flexibility allows it to depict the food processing system dynamics in the current environment better. The results also reveal a non-linear and interactive relationship between energy intensity and waste intensity and OEE, thus suggesting that the two factors should be approached mutually when designing optimization and managerial-operation strategies.

Although the validation carried out through polynomial regression affirms the reliability of the results of optimization, the study also shows what it is possible to further improve. The fact that prison and optimized OEEs correlate just perfectly indicates that the current model is definitely appropriate for the present set of data, but it apes no account of factors outside the model such as the nature of the specific machine, physical environmental conditions and other such influences. They might also serve as valuable input for inclusion in future models that would improve on the current state of the art prediction system.

The study confirms that there is a need to incorporate optimization algorithms with analytical validation procedures in tackling multi-objective issues in production systems. The goal of the optimization model is achieved in the sense that it combines the objectives of high OEE, low energy and waste at the same time while the regression model offers a valid platform to test this finding. Combined, these approaches provide methodologies that capture the key areas of change needed to enhance the food processing operations while also establishing the validity of the provided solutions.

Altogether, it is clear that the polynomial regression model verifies the optimization results by providing precise OEE values that are achieved during an optimization process. The obtained results have shown that the predictions made by the model have good agreement with the optimized values, thereby reflecting the validity of the optimization model to estimate the interdependencies between the energy consumption, waste generation and OEE. As much as the results of the regression model verify these relationships, it validates the preserving of energy consumption and waste for improving the overall function. As a backdrop to this research, the importance of combining the optimization approach with analytical validation for the creation of efficient and sustainable food processing systems is underscored.

Conclusion

The research implemented a model aimed at enhancing production capabilities, optimizing performance, conserving waste simultaneously. These objectives help ensure that machinery is utilized effectively across various product types. Analysis of overall equipment effectiveness (OEE), energy use and overall waste revealed notable discrepancies among different products and machines, indicating that certain machines may not be well-suited for specific products, potentially leading to production downtime and quality issues. By employing scheduling model, tasks can be assigned to machines that consume less energy, further reducing overall energy consumption and also by adjustments in operational settings and schedule could help mitigate excessive waste and inefficiencies.

Contribution to knowledge

The research makes significant contribution to the field of manufacturing efficiency optimization by uncovering intricate interactions and trade-offs in the food processing performance metrics, linking them to operational decisions and proving that multi-objective optimization combined with thorough validation is crucial for attaining optimal production efficiency.

References

Braid, T.K., Nwobi-Okoye, C.C., Ezechukwu, V.C., Uche, R., (2023) multi-objective optimization of novel AI-Si-Mg nanocomposite: a Tagushi-ANN-NSGA-II approach. *Journal of Engineering Research, 2023.*

Brayan, B.A., Mendoza, M., Juan M.M., (2022) Impact of the Application of Lean Manufacturing in Sausage production in the food manufacturing Industry in Metropolitan Lima: 3rd South American Internal Conference on Industry Engineering and Operations management. Doi:10.46254/SA03.20220336

Chen, S.C; Chen H.M.; Chen H.K.; Chieh C.L (2024), Muti-objective Optimization in Industry 5.0; Human-Centric AI Integration for Sustainable and Intelligent Manufacturing. Process 2024, 12, 2723. https//doi.org/10.3390/pr12122723.

Danishvar, M.; Danishvar, S.; Katsou, E.; Mansouri, S.A.; Mousavi. A. Energy-aware flow shop scheduling: A case for AI-driven sustainable manufacturing. IEEE Access 2021, 9, 141678-141692 [CrossRef].

Esteban, A.C.; Cesar, A.R.; Eduado, S.R.; Julian A.G (2025), Advancing Optimization Strategies in the Food Industry: from Traditional Approach to multi-objective and Technological Integrated solutions: Journal/ Applied Science/ volume 15/ issue 7/10.3390/app15073846.

Fan Z., Yuemin W., RUQING G., and Binghui T., (2025). Multi-Objective Optimization method for High- Efficiency and Low-Consumption Wire Rope Greasing Process. *https://doi.org/10.3390/s25072053*

Ifeanyechukwu U.O., Nwachukwu O.U., Ezechukwu V.C., Ifunanya M.O., and Chukwuma J.N., (2024) Modeling and optimization of Banana /Plantain Fiber extraction system, through dimensional analysis. *International Journal of Applied and Natural Science*

Igbokwe, N.C.; Charles, O.N.; Godwin, H.C.; and Mba, W.; (2025) Optimization of Overall Equipment Effectiveness factors in a food manufacturing small and medium enterprise. *Research in Engineering and Applied Science, 10* (1), pp836-845. Hal-04999684

Jiagi, Z., Han., Xin., Lili., Shun, J., Zhigang, J., Xiangmin, J., Kec-Hung, Lair, and Weicai, (2023) multi-objective optimization for energy saving and high efficiency production oriented multidirectional turning basesd on improved algorithm considering energy, efficiency and quality: *https://doi.org/10.1016/energy. 2023. 129205., volume 284, / December 2023, 129205.*

Madani, B., Saeed, M.Q., Abudulaziz, T.A., (2024) advancing manufacturing efficiency: Multi-objective optimization in the industry 5.0 Era. *Reality and Science Fiction in Education, Jan 2024 Jadda, Saudi Arabia. Hal-04397360*

Sandra, C.; Cerda, F; Arturo, A; Rojas, p; Fabricio, N.R; (2022) Application of multi-objective optimization of Industrial processes: A Literature Review process 2022. 10’133.https//doi.org/10.3390/pr10010133.

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