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Optimization parameters for the cotton swab process using hybrid MCDM methods based on response surface methodology

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ABSTRACT

Productivity improvement is a more complicated and challenging issue to resolve. There is a solution to the multi-response optimization problem. This study proposes a novel approach to optimizing parameters in the cotton swab process using a hybrid Multiple criteria decision-making (MCDM) method based on Response surface methodology (RSM). Simultaneously enhance decision-making efficiency by integrating Technique for order preference by similarity to ideal solution (TOPSIS) and Weighted aggregated sum product assessment (WASPAS) methodology. The optimal conditions were a speed rate of 1300 rpm, a thickness of 1.5 g/m, and a slidver gap of 20 cm, while the defect and downtime were 2.54 kg and 360.67 mins, respectively. The confirmation demonstrates that the actual practical and predicted results were similar. The proposed method's total cost improves from condition A to condition B by 33.86% and 2.45%, respectively. Furthermore, the energy consumption of cotton was found to be 6,208.08 MJ. The total energy consumption may be divided into three main categories: electric energy, thermal energy, and manual energy, which account for 43.12%, 55.73%, and 1.15%, respectively. The entropy reaches its maximum value in the drying and packaging units, which have inefficiencies of 91.24% and 4.35%, respectively, while the combined inefficiencies in the other five units are only 4.41%. This study contributes to advancing decision-making processes and offers insights for enhancing operational efficiency in the pharmaceutical or other manufacturer sector.

Keywords: Energy consumption, Multiple criteria decision-making, Response surface methodology, Weighted aggregated sum product assessment

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1. INTRODUCTION

The pharmaceutical industry is a critical component of the medical field. This is particularly apparent during the COVID-19 pandemic, a global health issue that negatively impacts individuals worldwide (Kunovjanek et al., 2021). In the fight against the transmission of this pathogen, the use of technological advances and materials in the medical and scientific fields is necessary to contain the transmission of this virus. The pharmaceutical field uses cotton swabs as valuable materials for COVID-19 prevention and treatment, as well as for virus analysis (Rokooei et al., 2022). Cotton swabs, a beneficial material for medical therapy, have a long history in medicine (Chadaga et al., 2021). At the same time, the crisis has led to a surge in demand for cotton swabs, resulting in a shortage of production capacity (Jauhari et al., 2017). In this study, we conducted a problem analysis. The aim of implementing the multi-response optimization (MRO) problem (Sriburum et al., 2023) in manufacturing cotton swabs in Thailand is to minimize losses of machines and raw materials. This results in appropriate production quantities and improves productivity in the pharmaceutical sector (O'Mahony et al., 2023). MRO problems require concurrently optimizing multiple goals or responses (Sharma et al., 2020). The need for MRO arises from the inherent complexity and uncertainty surrounding decision problems (Kundu et al., 2016; Zhao et al., 2022) in diverse fields such as engineering (Majumder et al., 2014), management (Zhou et al., 2022), economics (Jeong et al., 2022), environmental studies (Stefanini et al., 2022), and public policy (Vazquez Hernandez et al., 2023). This is problematic because finding a solution that satisfies all responses is difficult due to compromises between alternatives (Stević et al., 2020). By giving each objective a weight, multiple-response optimization methods like the weighted sum technique turn MRO problems into single-objective problems (Jeong et al., 2024). Evolutionary algorithms use selection, mutation, and crossover operators to find new solutions (Deng et al., 2021; Hua et al., 2021). Goal programming (GP) uses deviational variables to optimize the objective function (Hocine et al., 2020; Kouaissah et al., 2020). And multi-criteria decision-making (MCDM) (Emovon et al., 2021) is a strategy that looks at and evaluates possible solutions by using tools for decision-making (Koohathongsumrit et al., 2022; Wicaksono et al., 2022).

MCDM, a robust analytical framework, assists decision-makers in selecting the most suitable alternative from a set of options (Ghaleb et al., 2020), considering multiple conflicting criteria or objectives (Sotoudeh-Anvari, 2022). In many real-world scenarios, decisions involve cost, quality, time, and risk trade-offs. The techniques offer systematic approaches to navigate this complexity and facilitate informed decision-making (Sahoo et al., 2023). Traditional decision-making approaches, often based on single criteria or simplistic heuristics, may overlook critical dimensions of the problem or fail to account for stakeholders' preferences and uncertainties. Therefore, MCDM is a systematic method for making decisions that includes establishing decision criteria, measuring the performance of different options, evaluating trade-offs, prioritizing alternatives, and dealing with ambiguity (Chowdhury et al., 2020). These also allow for sensitivity analysis, which evaluates the resilience of decision outcomes to changes in criteria weights or input data. Additionally, it offers tools to tackle uncertainty by utilizing probabilistic modeling, scenario analysis, or optimization methods. MCDM uses many methods, including analytic hierarchy process (AHP), TOPSIS, Electre, and PROMETHEE (Sałabun et al., 2020). Each has benefits and works best in certain decision situations, depending on criteria, preferences, and available data.

The literature discovered that decision analysis frequently uses the Technique for order preference by similarity to ideal solution (TOPSIS) method, an MCDM technique, to determine the optimal alternative by considering various criteria. Each criterion has distinct units. The additional study is as follows: This study explores the TOPSIS method's limitations and theoretical underpinnings using simulation and experimental analysis, emphasizing the importance of selecting the right decision-making approach for individuals and businesses (Çelikbilek et al., 2020). The study introduces a MCDM approach to prioritize industrial arc welding robots, demonstrating its value in choosing suitable industrial robots (Chodha et al., 2022). The study explores TOPSIS, a materials science and engineering decision-making strategy to optimize competitive supply chains in eleven Indian sectors (Singh et al., 2023). It provides a comprehensive framework and compares outcomes with other MCDM techniques. The paper comprehensively assesses green outsourcing by applying MCDM approaches (Liaw et al., 2020).

For improved decision-making clarity, providers are classified into four distinct tiers using DEMATEL, inter-criteria correlation, and classifiable TOPSIS approaches. Using FAHP-FTOPSIS, the study ranks 21 barriers to sustainable manufacturing in SMEs (Abdullah et al., 2023). Insufficient legislative enforcement, 6R application issues, control systems, carbon audits, and dependence on fossil fuels are significant impediments. Lean, environmentally friendly production, and industry-standard evaluation are effective tactics. The study uses AHP and TOPSIS to compare green manufacturing adoption ranks to identify decision-making factors in a globalized economy (Singh et al., 2020). Furthermore, the MCDM method incorporates a unique approach known as the weighted aggregated sum product assessment (WASPAS). WASPAS is a methodical approach for evaluating multiple criteria and making decisions, particularly useful in strategic business planning, project selection, and policy formulation, assisting decision-makers in navigating complexities. The research investigates the influence of spot-welding parameters on the tensile-shear force of steel and aluminum sheets (Bagal et al., 2021). It reveals that employing WASPAS and input parameters can enhance the joint's strength, with welding current and time playing crucial roles in determining the outcome.

This study utilizes MCDM to rank five aluminum metal matrix composites (AMMCs) based on their weight percentages of coconut shell ash (Sapkota et al., 2023). The entropy technique generates weights for criteria, and all

MCDM methods suggest a 15% CSA+Al composite. The EDAS, MOORA, and WASPAS MCDM approaches exhibited a perfect correlation of 100%. This study demonstrates that the mechanical characteristics of resin-bound sand molds and cores improve with more binder and longer curing times but degrade with finer grain size (Behera et al., 2022). WASPAS improved the results, laying the groundwork for optimizing molding settings to produce high-quality metal components. This study aims to develop a decision support system, based on the WASPAS method, to assist motorbike owners in selecting the most suitable engine oil for 150 cc sports motorbikes (Hutagalung et al., 2022). The system intends to enhance friction and engine performance. This study assesses the efficacy of two optimization methods (Panda et al., 2023), WASPAS and the Multi-Objective Genetic Algorithm, in wire electric discharge machining. The evaluation uses Taguchi's L9 orthogonal array for exponential trend line analysis. The study created a decision matrix, compared the ranking results from the WASPAS and VIKOR methodologies (Altın, 2020), and compared them with the ranking of the life quality index. The findings indicated that the approaches were highly favorable and interchangeable with the values, proving the validity of the index.

Despite its common use in decision-making, WASPAS is not without its limitations. One of the primary critiques is the inherent subjectivity in the process of allocating weights to each criterion. Various decision-makers may allocate various weights based on their individual biases or viewpoints, resulting in potentially biased results. Therefore, the principal contribution of this study is to employ a hybrid MCDM approach to enhance decision-making efficiency (Alizadeh et al., 2020). This new method combines TOPSIS with linear programming and the WASPAS method, which is based on the Response Surface Methodology (RSM) (Sreeraj et al., 2022). It works well even when decision data is uncertain or changes over time. Simultaneously, RSM is essential for designing experiments, modeling intricate systems, and optimizing processes. It improves performance and productivity in a wide range of fields. The models are utilized to determine the most favorable conditions for response variables, employing strategies such as gradient-based methods, desirability functions (Dutta et al., 2024), or numerical optimization algorithms.

The case study assessed optimal conditions. The analysis includes the collection of relevant data related to machine productivity, which influences the efficiency of cotton swab manufacturing. Key performance metrics are established to evaluate defects and downtime. Meanwhile, root cause analysis techniques (Sakdiyah et al., 2022), such as Pareto analysis, fishbone diagrams, or 5-whys analysis, can help identify the primary reasons for production. Then, we can optimize the process using the hybrid MCDM approach, which involves adjusting machine settings to streamline operations and increase throughput. Energy is crucial for generating and providing the necessary power for production processes. Moreover, it constitutes a significant portion of manufacturing costs and plays a role in the emission of greenhouse gases. Particularly, it pertains to the creation and application of electrical, thermal, and manual energy (Mousavi et al., 2016; Yusuf et al., 2021). For long-term sustainability, the research has focused on improving efficiency, reducing manufacturing costs, and addressing environmental concerns related to energy usage in production. The production planning process can utilize power analysis of machinery and plants to generate distinct power predictions for each unit. We allocate resources optimally for strategic production, planning, and energy efficiency control, thereby maximizing our potential (Dietmair et al., 2009; Sweeting et al., 2011). The focus is on optimizing the energy efficiency of the chosen machine or industrial system. The significance of machine reliability and decreased production time has been emphasized to enhance efficiency in industrial manufacturing.

The following paragraph describes the study's framework (Fig. 1). Section 2: outlines the research approach and discusses the utilization of the RSM, TOPSIS, and WASPAS methodologies. Section 3: Determining the optimal operating parameters by integrating the TOPSIS and WASPAS concepts with RSM methods is the objective of the proposed method and the energy consumption analysis phase of the factory. Section 4 contains a conclusion, limitation and future work.

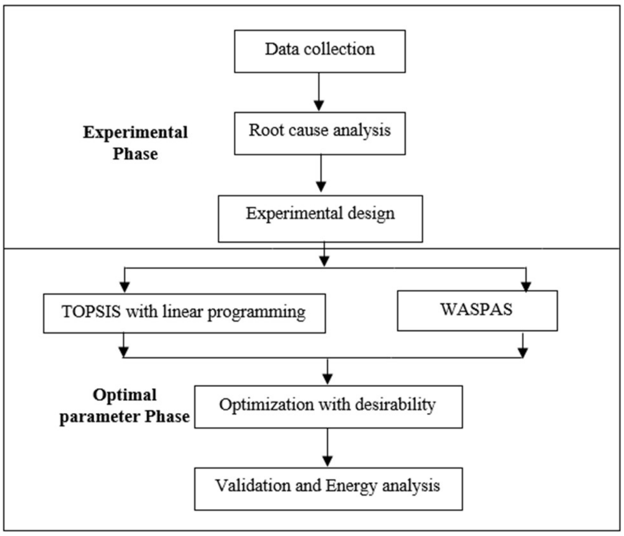


Fig. 1. The framework of this paper

2. MATERIALS AND METHODS

2.1 Cotton Swab Process

There are three primary stages to the process, as shown in Fig. 2.

(1) Slidver process: lint and fuzz are manufactured from cotton orders. Pure and genuine. To satisfy quality standards, 16–18 mL. Fibers are bleached and broken. Before making cotton swabs, high-quality fibers undergo a carding process to adjust their size.

(2) Plastic rods: The factory in the case study combines

paint and glue with plastic resins purchased from the manufacturer. It is hollow molded using plastic rod injection. A cutting machine will transform molded plastic into regular plastic rods. The factory sends the scattered and untidy plastic stems to the stem consolidation department, which then combines them into bags. Inspect for standard size and strength.

(3) Before entering the next cotton swab manufacturing process, third step is to combine cotton swabs after obtaining the raw materials from steps (1) and (2), a head wrapping machine mixes the raw materials with glue to produce cotton swabs. The exam will use a sample acceptance plan as a decision criterion.

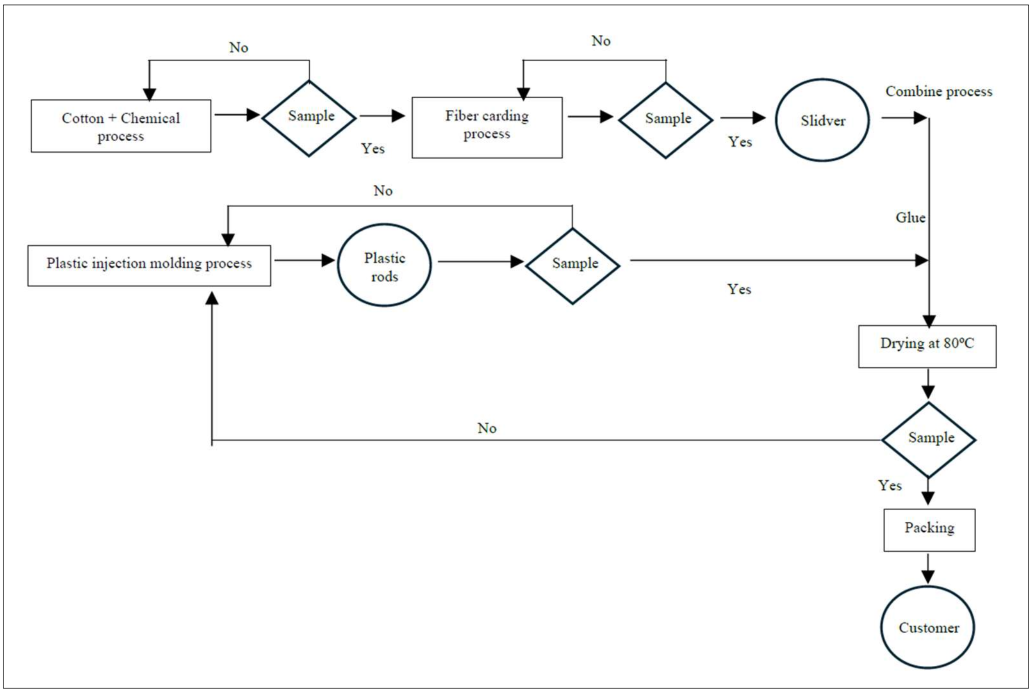


Fig. 2. Operation process chart of cotton swab

2.2 Root Cause Analysis

Identifying and analyzing problems. The case study indicates that equipment defects and delays resulted in a decrease in productivity. Through conducting interviews with production managers, quality engineers, and employees, researchers can ascertain the underlying cause of the problems and validate their impact on productivity. The example employs a 5-whys analysis of defects, as illustrated in Fig. 3.

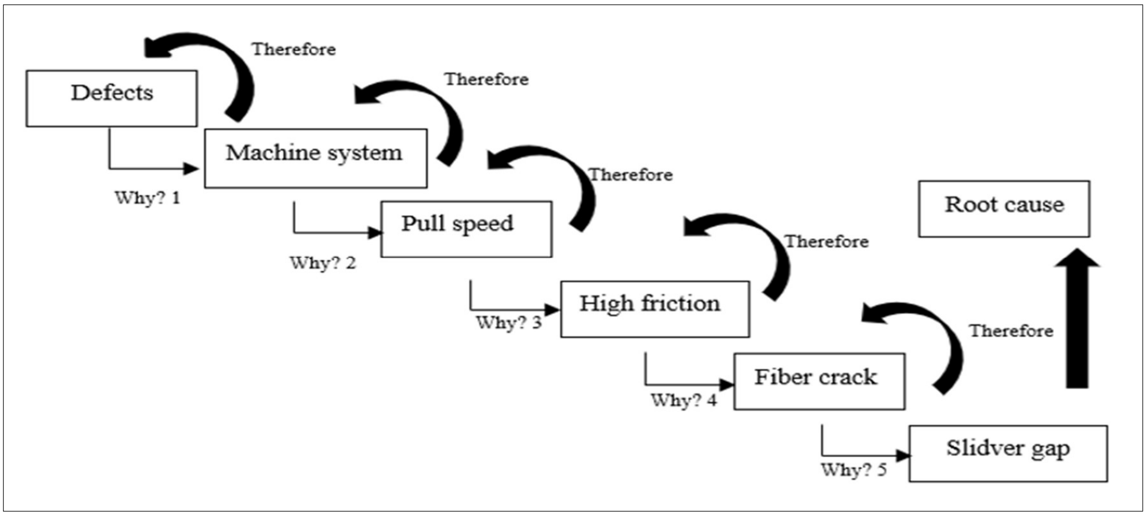


Fig. 3. Five-whys analysis of defects

The examination conducted using the 5-whys method revealed that the variables speed rate, thickness, and slidver gap, which influence defects and downtime, align with the functioning of the factory under investigation. Further analysis is to follow. In Fig. 4. the plastic rod is not bonded and becomes entangled with the slidver, causing problems during the production process

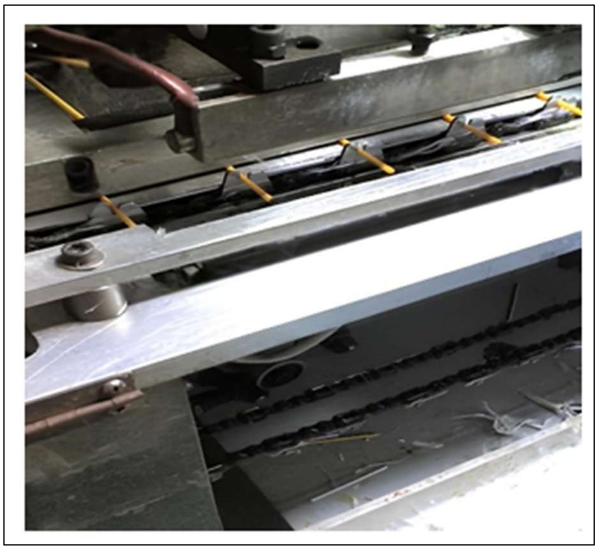


Fig. 4. Defects in production result in machine downtime

2.3 RSM and Experiment Design

RSM is invaluable for designing experiments, modeling intricate systems, and optimizing processes in various industries (Li et al., 2021). The systematic approach of investigating and analyzing the interactions between variables makes it an essential tool for researchers and practitioners who want to improve their processes and products. The primary objective of the RSM is to identify a reliable estimation for the functional correlation between independent and response variables. The quadratic model is sufficient for the optimum region. It employs experimental designs such as the central composite design (CCD) or the box-behnken design (BBD) to pinpoint crucial factors influencing interactions, steer subsequent experiments, and pinpoint any gaps. The BBD is a more economical and practical alternative to the CCD (Alıemeke et al., 2020). However, it requires three levels for each component, reducing the number of experimental trials required to study many factors. The BBD was the experimental framework, which comprised three levels of coding for each variable and three components. A non-linear regression approach was used to reveal relevant model terms that fit the model. Assigned to the obtained mathematical model is Equation (1).

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

$\hat{Y}$ is the predicted response, β_0 the offset term, β_i the linear effect, β_{ij} the squared effect and β_{ii} is the interaction effect. The RSM optimization was carried out using the desirability function provided in Equation (2):

$$D = (d_1 \times d_2 \times \cdots \times d_m)^{1/m} \quad (2)$$

Where, d is the desirability and m are the no. of responses. In individual desirability (d_m), the parameters optimize a solitary response and a collection of composite desirability (D). The purpose of computing the desirability function was to minimize defects and downtime. The most desirable settings were determined by selecting the tasks with the highest desirability value. This study investigates the impact of two independent variables on developing and optimizing cotton swab manufacturing. BBD and RSM are employed for this purpose. As demonstrated in Table 1, the data analysis comprises three factors and three levels. Minitab and Design Expert were utilized to analyze the parameters. The present study comprised a total of seventeen trials.

Table 1. The parameters for experiments

Factor	Unit	Symbol	Levels		
			-1	**0**	**1**
Speed rate	rpm	A	1300	1400	1500
Thickness	g/m	B	1.3	1.4	1.5
Slidver gap	cm	C	20	30	40

2.4 A Novel TOPSIS

The concept of TOPSIS linear programming is converted to an equivalent form (Hajduk, 2021; Pawaree et al., 2024). This evaluation aims to assess the efficiency of the iteration proximity. y_{ij} is the normalized performance of option i with respect to criterion j. Equations (3) and (4) compute the normalized performance of options i and j regarding the benefit and cost criteria, respectively.

$$\text{Beneficial criteria:} \quad y_{ij} = x_{ij} \Big/ \sqrt{\textstyle\sum_{i=1}^{n} x_{ij}^2} \quad (3)$$

$$\text{Cost criteria:} \quad y_{ij} = 1 - \left(x_{ij} \Big/ \sqrt{\textstyle\sum_{i=1}^{n} x_{ij}^2} \right) \quad (4)$$

The weights of relevant criteria are denoted by w_j based on decision maker. The optimal weights for aggregating the distances between the ideal solution in the negative and the ideal solution in the positive, while taking alternative i into account, are represented by the variables as λ_i^- and λ_i^+. Let y_i^- and y_i^+ denote the negative and positive ideal values, respectively, for each criterion j.

$y_i^- = \min\{y_{ij}\}\ \forall$ j, and $y_i^+ = \max\{x_{ij}\}\ \forall$ j, j = 1, 2, ..., m. The relative closeness coefficient value (CC_i) for a set of alternatives i ($1 \le i \le n$) can be defined by Equation (5):

$$\mathrm{CC_i} = \frac{\lambda_i^-\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_{ij})^2-(y_j^-)^2\right)}\right)}{\lambda_i^-\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_{ij})^2-(y_j^-)^2\right)}\right)+\lambda_i^+\left(\sum_{j=1}^{m}\sqrt{w_j^2\left((y_j^+)^2-(y_{ij})^2\right)}\right)} \tag{5}$$

$\lambda_i^- = \lambda_i^+$; λ_i^-, $\lambda_i^+ \geq 0$, $j = 1, 2, \ldots, n$.
$w_j \geq 0$, $j = 1, 2, \ldots, m$.

This is among the most prevalent methods for solving decision problems related to issues involving multiple responses. Utilizing MATLAB and LINGO, the mathematical equations were computed.

2.5 WASPAS

WASPAS is a novel combination of the weighted sum model (WSM) and weighted product model (WPM) (Ali et al., 2021), which are common in MCDM. The decision matrix is normalized using Equations (6) and (7).

$$\text{Beneficial criteria: } \bar{x}_{ij} = \frac{x_{ij}}{Max_i x_{ij}} \tag{6}$$

$$\text{Non-beneficial criteria: } \bar{x}_{ij} = \frac{Min_i x_{ij}}{x_{ij}} \tag{7}$$

Step 1. WASPAS is a common MCDM method that considers mean weighted success and total relative importance to find the best solution. Like WSM, it assesses numerous alternatives using decision criteria. For the entire relative significance of the ith choice, apply in Equation (8):

$$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij}\, w_j \tag{8}$$

w_j is the relative significance of the j^{th} criterion while the WPM method evaluates the total relative significance of the i^{th} alternative is calculated in Equation (9):

$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j} \tag{9}$$

Step 2. The integrated utilization of both additive and multiplicative types of aggregation enhances the accuracy of ranking. The assessment of the i^{th} alternative is carried out as follows:

$$Q_i = \lambda_i Q_i^{(1)} + (1-\lambda_i) Q_i^{(2)} = \lambda_i \sum_{j=1}^{n} \bar{x}_{ij} w_{ij} + (1-\lambda_i) \prod_{j=1}^{n} (\bar{x}_{ij})^{w_j}, \lambda_i = 0, 0.1, \ldots, 1 \tag{10}$$

λ_i is the combination parameter, WASPAS ranks candidate alternatives by Q value, with the best decision obtaining the highest Q value. Setting λ to 0 results in the WPM method, while increasing it to 1 transforms it into the WSM method.

Step 3. Enhancing the accuracy of the WASPAS methodology was the subject of a proposal. If the errors in determining the starting criteria values are stochastic, the alternatives' fluctuations depend upon the variances of WSM and WPM. Determining the optimal value of λ in a decision-making context appears to be an exceedingly difficult task. To find the extreme function, we can set the derivative of Equation (10) concerning λ to 0. Therefore, it is possible to determine the most advantageous values of λ using the subsequent method:

$$\lambda = \frac{\sigma^2(Q_i^2)}{\sigma^2(Q_i^{(1)})+\sigma^2(Q_i^{(2)})} \tag{11}$$

The variances, denoted as $\sigma^2(Q_i^{(1)})$ and $\sigma^2(Q_i^{(2)})$ can be computed using the equations shown below:

$$\sigma^2(Q_i^{(1)}) = \sum_{j=1}^{n} w_j^2\, \sigma^2(\bar{x}_{ij}) \tag{12}$$

$$\sigma^2(Q_i^{(2)}) = \sum_{j=1}^{n} \left[\frac{\prod_{j=1}^{n}(\bar{x}_{ij})^{w_j} w_{ij}}{(\bar{x}_{ij})^{w_j}(\bar{x}_{ij})^{(1-w_j)}}\right]^2 \sigma^2(\bar{x}_{ij}) \tag{13}$$

The method used for determining the variances of the normalized establishing criteria values in a normal distribution with a confidence level of 0.05 is as follows:

$$\sigma^2(\bar{x}_{ij}) = (0.05\bar{x}_{ij})^2 \tag{14}$$

2.6 Production Energy Consumption

The following approaches were utilized to comprehensively analyze the operational data collected. An evaluation was carried out to study the energy utilization in unit operations with the purpose of examining the pattern of energy distribution and consumption. A study was done to determine the main unit of energy consumption by analyzing the percentage distribution of total energy consumption. Statistics capture was employed to generate energy consumption statistics for different units throughout the study period.

2.6.1 A Generic Energy Consumption

The cotton production method entails the use of steam, chemical agents, and manual labor to facilitate the process. To streamline the data collection method, the production process was divided into 8 discrete unit processes. The essential attributes for evaluating energy in every individual step of cotton processing were acquired either via direct measurements or collected from the production facility. A comprehensive inventory was carried out to record the motors and their matching power ratings for the equipment (Odunfa et al., 2022). The factory's energy department provided most of the parameters. Data was gathered from the factory for a duration of 4 months. The measuring quantities employed during the data gathering procedure include; (1) a device used to measure the duration of time in separate segments; (2) a tachometer to gauge the velocity at which the cotton is being wound; (3) a weight balance to quantify the amount of cotton. The results underwent error analysis. The equation provided is as follows:

$$error = \frac{measured\ value - true\ value}{true\ value} \times 100\% \quad (15)$$

2.6.2 Application of Energy Consumption

The energy components of a certain quantity of cotton were determined using the following methodology:

Assessment of Electrical Energy:

The electrical energy consumption of the equipment was determined by multiplying the rated power of each motor by the total number of operational hours. The electrical inputs were calculated using an expected motor efficiency of 80%.

$$E_p = \eta Pt \quad (16)$$

where E_p is the electrical energy consumed (kWh), P the rated power of motor (kW), t the hours of operation (h) and η the power factor (assumed to be 0.8).

Assessment of Manual energy

This estimate was calculated based on the values that were suggested. The maximum continuous energy consumption rate is 0.30 kW, with a conversion efficiency of 25%. The mean power output of an average human worker in tropical regions is approximately 0.075 kW.

$$E_m = 0.075Nt \quad (17)$$

where E_m is the manual energy consumed (kWh), 0.075 is the average power of a normal human labour (kW), N the number of persons involved in an operation and t the useful time spent to accomplish a given task (h).

Assessment of Thermal Energy:

The thermal energy derived from fossil fuels is used to power the internal combustion engine. The quantity of diesel used in the steam boiler was calculated by multiplying the fuel consumption by the calorific value of the fuel.

$$E_t = C_f W_f \quad (18)$$

where E_t is the thermal energy consumed (J), C_f the calorific value of fuel used (J/kg) and W_f the quantity of fuel used (kg).

Total Energy Input

The energy input for each unit operation is given as follows:

$$E_{seo} = E_p + E_m + E_t \quad (19)$$

Where E_{seo} is the total energy input (kWh), E_p is electrical energy input (kWh), E_m is manual energy input (kWh), E_t is the thermal energy consumed (kWh).

Energy consumption

The power plant's generators and boiler utilize this entire amount of energy. The computation is obtained using the following formula:

Energy Consumption = Units Wattage x Number of Hours Used.

$$EC = Pt \quad (20)$$

Where EC denotes the energy consumption (J), P denotes the power ratings for each unit (kW), t denotes the operational time (h).

The energy expended during inactive processes, such as the initiation of a facility. The shutdown and plant cleaning and sterilization processes have been included in the energy sequestered in each of the operations.

2.6.3 Enthalpy and Change in Enthalpy

Thermal energy released by steam is quantified by a characteristic called enthalpy (H). The thermal effect for the reactions at constant pressure is derived from the enthalpy of vaporization. Enthalpy difference refers to the thermal energy differential between the vapor and liquid phases of steam.

2.6.4 Model Equations for Exergy

The exergy Ex for a closed system can be specifically described mathematically as;

$$E_x = V(p - p_o) - S(T - T_o) - \sum_i n_i (\mu_i - \mu_{io}) \quad (21)$$

The exergy of a fluid flowing across the internal limits of an open system may be expressed as;

$$E_x = (H - H_o) - T_o(S - S_o) - \sum_i \mu_i (n_i - n_{io}) \quad (22)$$

where,

$$H = U + p_o V \quad (23)$$

The preceding equations include the extended quantity, U denotes the internal energy, S the entropy, H the enthalpy, V the volume and n_i the number of moles of substance, i the intensive quantity, T the temperature, p the pressure and mi the chemical potential of the substance i. The subscript ‘‘o’’ denotes the conditions of the reference environment. Equations (21) and (22) include a third factor that considers the contribution resulting from the chemical change of the system. This concept is disregarded in this investigation as the procedures performed did not entail any chemical reaction.

The difference in exergy ΔE_x between the outgoing and incoming streams in a steady flow process is precisely specified as:

$$\Delta E_x = \dot{W}_u - T_o \dot{R}_s \quad (24)$$

where $\dot{W}_u$ is the useful work, R_s the production of entropy and T_o the ambient temperature e. The exergy difference ΔE_x is defined in terms of each component exergy $e_{x,q}$ per unit mass and the mass flow rate w_q:

$$\Delta E_x = \sum_{q_{out}} w_q e_{x,q} - \sum_{q_{in}} w_q\, e_{x,q} \quad (25)$$

The exergy of each component is defined as,

$$e_{x,q} = h_q - T_o s_q \quad (26)$$

It is evident from Equation (24) that the exergy change is a trade-off between the useable work and the entropy production term, which represents the work wasted due to irreversibility's. Concerning a reversible procedure, $\dot{R}_s$= 0 and thus, A reversible process exergy change is equivalent to either the maximum useful work associated with a work-producing process or the minimum useful work required by a work-consuming process. The above information clearly indicates that the variations in exergy and the generation of entropy serve as the energy limits for the process or a group of processes.

2.6.5 Utility Exergy

The use of primary utilities, including fuel, cooling water, steam, hot air, and electricity, is the inevitable outcome of all energy demands. Electrical utilities are encompassed within the category of beneficial work, $\dot{W}_u$, term. Process streams encompass raw materials, products, wastes, and intermediate materials that are generated during the subsequent transformation of the raw materials. To achieve an energy-efficient design, it is frequently preferable to segregate the heating and cooling utilities streams from the process streams outlined in Equation (24). It can be deduced that:

$$\Delta E_{x,proc} = \dot{W}_u + \Delta E_{x,util} - T_o \dot{R}_s \quad (27)$$

The variation in utility exergy $\Delta E_{x,util}$, specifically applicable to steam in this study, can be calculated using the following formula:

$$\Delta E_{x,util} = H_{util,1} - H_{util,2} - T_o\left(S_{util,1} - S_{util,2}\right) \quad (28)$$

The enthalpies and entropies of steam can be estimated using the conventional data table. The exergy change of the process stream can be calculated by using Equations (24) and (25), which can be assessed using the tabular data for enthalpies and entropies or by utilizing predictive equations derived from the specific heat capacity parameters. For the scenario of constant specific heat capacity and insignificant residual exergies over the temperature range under consideration, the most straightforward equation to determine the exergy changes (Waheed et al., 2008).

$$e_{x,2} - e_{x,1} = c_p(T_2 - T_1)\left[1 - \frac{T_o}{(T_2-T_1)_{ml}}\right] \quad (29)$$

where,

$$(T_2 - T_1)_{ml} = \frac{T_2-T_1}{\ln(T_2/T_1)} \quad (30)$$

The specific heat constant of cotton may be calculated using the following mathematical relationship:

$$c_p = c_{ml}(0.3823 + 0.6183x_m) \quad (31)$$

where x_m is the weight fraction of cotton.

2.6.6 Inefficiency

Exergy research enables a more thorough analysis of a system by identifying the specific locations within the system where exergy is lost due to internal irreversibility and its underlying causes. Inefficiency may be defined as the proportion of irreversibility in each individual segment to the total irreversibility across all sections. This is mathematically defined as

$$I_k = \frac{(T_o\dot{R}_s)_k}{\sum_k^{all\ sections}(T_o\dot{R}_s)_k} \quad (32)$$

2.7 Energy Production and Electricity Generation from Fossil Fuels

Shaft work is derived from the operation of electric and fossil-fuel furnaces (Dincera et al., 2004). The efficiency for generating shaft work from electricity is as follows:

$$\eta_{m,e} = W/W_e \quad (33)$$

$$\psi_{m,e} = E^W/E^{W_e} = W/W_e = \eta_{m,e} \quad (34)$$

Fuel efficiencies are as follow:

$$\eta_{m,f} = W/m_f H_f \quad (35)$$

$$\psi_f = \frac{E^W}{m_f \varepsilon_f} = W/m_f \gamma_f H_f \cong \eta_{m,f} \quad (36)$$

Efficient energy generation from fossil fuels is characterized by:

$$\eta_{e,f} = W_e/m_f H_f \quad (37)$$

$$\psi_{e,f} = E^{W_e}/m_f \varepsilon_f = W_e/m_f \gamma_f H_f \cong \eta_{e,f} \quad (38)$$

Consequently, it can be deduced that the exergy efficiencies for the process of generating electricity can be considered equal to the corresponding energy efficiencies.

The efficiency of the mechanical energy generation systems powered by fossil fuels, which produce a change in kinetic energy Δke in a stream of matter m_s, they are as follows:

$$\eta_{ke,f} = m_s \Delta ke_s/m_f H_f \quad (39)$$

$$\psi_{ke,f} = m_s \Delta ke_s/m_f \varepsilon_f \quad (40)$$

$$\psi_{ke,f} = \frac{m_s \Delta ke_s}{m_f \gamma_f H_f \varepsilon_f} \cong \eta_{ke,f} \quad (41)$$

3. RESULTS AND DISCUSSION

3.1 Experimental for Cotton Swab Manufacturing

The experimental data matrix was utilized in the BBD technique. This study examines the effects of multiple factors on manufacturing of cotton swabs. There are 17 experiments show in Table 2.

The regression equation for the determination of predicted values of defect (R_1) and downtime (R_2) parameter, where A is speed rate (rpm), B is thickness (g/m), and C is slidver gap (cm), is given as follows (Uncoded):

$$R_1 = -449.925 + 0.56196A + 106.35B - 0.434125C - 0.0285AB + 0.0004725AC - 0.11BC - 0.0001899A^2 - 27.125B^2 - 0.00104C^2 \quad (42)$$

$$R_2 = 27371.325 - 44.919A + 3678.5B + 135.57C + 3.675AB - 0.13025AC + 30.25BC + 0.0154175A^2 - 3382.5B2 + 0.056750C^2 \quad (43)$$

Table 2. Experiment matrix with multi-response

Exp.no	Speed rate (rpm)	Thickness (g/m)	Slidver gap (cm)	Defect (kg)	Downtime (min)
1	1400	1.5	20	4.30	280
2	1500	1.3	30	5.53	354
3	1300	1.4	20	3.42	481
4	1300	1.3	30	4.10	521
5	1400	1.4	30	5.97	312
6	1500	1.5	30	2.59	482
7	1400	1.4	30	5.88	341
8	1300	1.5	30	2.30	502
9	1400	1.4	30	5.92	315
10	1400	1.3	40	6.77	292
11	1500	1.4	20	3.45	630
12	1500	1.4	40	5.12	267
13	1400	1.3	20	6.83	291
14	1400	1.4	30	5.59	374
15	1400	1.4	30	5.64	380
16	1400	1.5	40	3.80	402
17	1300	1.4	40	3.20	639

Table 3. ANOVA of cotton swab manufacturing

Source	Defect					Downtime				
	SS	DF	Mean Square	F-value	p-value	SS	DF	Mean Square	F-value	p-value
Model	32.1300	9	3.5700	35.5400	< 0.0001	207705.00	9	23078.42	9.1313	0.0041
A-Speed rate	1.6800	1	1.6800	16.7600	0.0046	21012.50	1	21012.5	8.3139	0.0235
B-Thickness	13.1100	1	13.1100	130.4700	< 0.0001	5408.00	1	5408	2.1398	0.1869
C-Slidver gap	0.0990	1	0.0990	0.9856	0.3539	840.50	1	840.5	0.3326	0.5822
AB	0.3249	1	0.3249	3.2300	0.1152	5402.25	1	5402.25	2.1375	0.1871
AC	0.8930	1	0.8930	8.8900	0.0205	67860.25	1	67860.25	26.8500	0.0013
BC	0.0484	1	0.0484	0.4818	0.5100	3660.25	1	3660.25	1.4482	0.2679
A^2	15.1800	1	15.1800	151.1000	< 0.0001	100083.91	1	100083.92	39.5998	0.0004
B^2	0.3098	1	0.3098	3.0800	0.1225	4817.39	1	4817.392	1.9061	0.2099
C^2	0.0453	1	0.0453	0.4511	0.5233	135.60	1	135.60	0.0537	0.8234
Residual	0.7032	7	0.1005	-	-	17691.70	7	2527.39	-	-
Lack of Fit	0.5838	3	0.1946	6.5200	0.0509	13622.50	3	4540.83	4.4636	0.0912
Pure Error	0.1194	4	0.0298	-	-	4069.20	4	1017.3	-	-
Total	32.8300	16	-	-	-	225397.52	16	-	-	-

In Table 3, the R^2 values of Equations (42) and (43) were 0.9786 and 0.9215, respectively, demonstrating a high level of accuracy in predicting the experimental results (Chicco et al., 2021). The regression model is derived from the BBD and utilizes the parameter dataset obtained from cotton swabs. The equation representing the relationship between the defect and downtime followed a quadratic model ($p < 0.05$). Furthermore, the p-values for lack of fit of the equation were not statistically significant (0.0509 and 0.0912). Verify that the model and experimental data correspond. The analysis of variance (ANOVA) results shows that the following defect model terms (linear, interaction, and quadratic coefficients) have significant effects ($p < 0.05$) on each response: A, B, AC, and A^2. In addition, the significant effect parameters for the downtime are as follows: A, AC, and A^2.

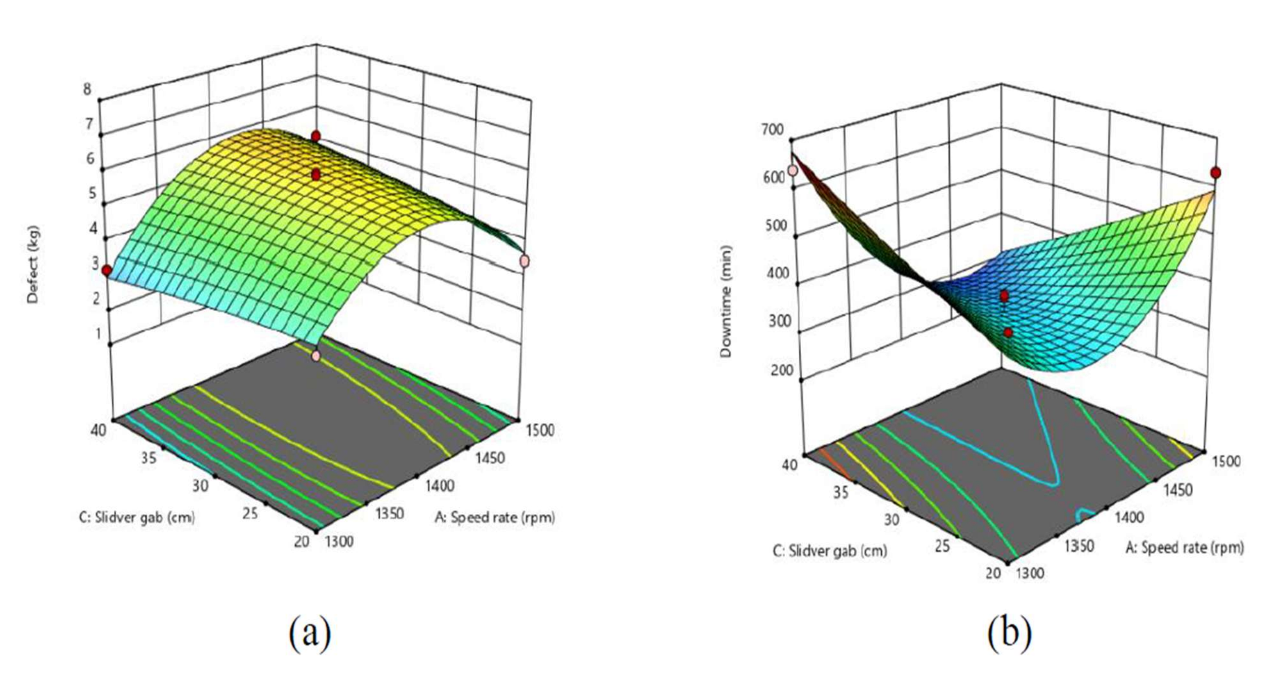


Fig. 5. The response surface plot between the speed rate and the slidver gap of (a) defect and (b) downtime

The defect and downtime regression model can be used to create a response surface plot (Majumder et al., 2014). In Fig. 5(a), the response surface plot illustrates the influence of speed rate (A) and slidver gap (C). The level of thickness (B) was set at zero. The defect increased significantly at level 0 with the interaction effect. The interaction effect was negatively correlated with the downtime. The influence of speed rate (A) and slidver gap (C) on downtime as shown in Fig. 5(b).

Finding the optimal parameters is complex. The two responses to the MRO problem have different points of view. Therefore, the hybrid MCDM approach solves this problem.

3.2 TOPSIS with Linear Programming

The procedure for normalizing the criterion is as follow: The R_1 and R_2 characteristics might be considered as cost criteria. The construction process can be transformed by Equation (4). The two responses can be converted into the CC_i scores, as shown in Table 4. Weight is set at $w_1 = 0.5$ and $w_2 = 0.5$.

For example, we used equation 5 to solve CC (no.9) using linear programming. As a result, the solution was 0.3209. This makes it possible to compute the remaining CC scores using the same methodology. The regression model for the CC is obtained with RSM as follows in terms of the uncoded equation ($R^2 = 0.7383$, adj $R^2 = 0.4021$):

$$CC = -2.59871834 + 0.017156A - 13.81246B + 0.01651C - 0.005281AB + 0.00005702AC - 0.06802BC - 0.0000039A^2 + 8.388965B^2 - 0.00006957C^2 \quad (44)$$

Table 4. The experimental results for the CC_i response

Exp. no.	Response matrix R_1	Response matrix R_2	CC
1	4.30	280	0.6008
2	5.53	354	0.4879
3	3.42	481	0.3128
4	4.10	521	0.2787
5	5.97	312	0.3211
6	2.59	482	0.3338
7	5.88	341	0.3155
8	2.30	502	0.3358
9	5.92	315	0.3209
10	6.77	292	0.3194
11	3.45	630	0.2106
12	5.12	267	0.3377
13	6.83	291	0.3192
14	5.59	374	0.3101
15	5.64	380	0.3079
16	3.80	402	0.3288
17	3.20	639	0.2117

3.3 WASPAS Method

The WASPAS method-based analysis for multi-response optimization (Bagal et al., 2021) of the considered cotton swab manufacturing. The process of normalizing the criterion involves the following steps: Equation 7 indicates that defect and downtime responses are non-benefit criteria

Table 5. Normalized decision matrix of WASPAS

Exp. no	Defect	Downtime	Q_1	Q_2	Q
1	0.5349	0.9536	0.7442	0.7142	0.7296
2	0.4159	0.7542	0.5851	0.5601	0.5730
3	0.6725	0.5551	0.6138	0.6110	0.6125
4	0.5610	0.5125	0.5367	0.5362	0.5365
5	0.3853	0.8558	0.6205	0.5742	0.5976
6	0.8880	0.5539	0.7210	0.7014	0.7118
7	0.3912	0.7830	0.5871	0.5534	0.5706
8	1.0000	0.5319	0.7659	0.7293	0.7478
9	0.3885	0.8476	0.6181	0.5739	0.5966
10	0.3397	0.9144	0.6271	0.5574	0.5978
11	0.6667	0.4238	0.5452	0.5315	0.5388
12	0.4492	1.0000	0.7246	0.6702	0.7024
13	0.3367	0.9175	0.6271	0.5559	0.5943
14	0.4114	0.7139	0.5627	0.5420	0.5529
15	0.4078	0.7026	0.5552	0.5353	0.5453
16	0.6053	0.6642	0.6347	0.6340	0.6344
17	0.7188	0.4178	0.5683	0.5480	0.5587

, and the decision maker sets the weight index at $w_1 = 0.5$, $w_2 = 0.5$ and $\lambda = 0.5$.

The comprehensive experimental plan, configuration of the process parameters. The normalized data can be transformed by equation (7). The total relative significance of Q_1 and Q_2 can be evaluated by Equations (8) and (9) respectively. The simultaneous optimization of all responses (Q) is demonstrating in Table 5. The regression model for the Q is obtained with RSM as follows in terms of the uncoded equation ($R^2 = 0.8444$, adj $R^2 = 0.6439$):

$$Q = 11.00597-0.003736A - 10.85354B - 0.049516*C - 0.001812AB + 0.000054381AC - 0.0246924BC + 0.0000017A^2 + 5.27987B^2 + 0.000136C^2 \tag{45}$$

3.4 Determining Optimal Parameters and Sensitivity Analysis

Desirability functions are highly effective tools for multi-criteria optimization and decision-making (Rajesh, 2021). Table 6 presents a mathematical model that employs the data matrix to determine the CC and Q values. The research concentrated on multiple responses, with productivity determining the decision to reply. The maximum desirability is 0.9560 ($R^2 = 0.8849$, adj $R^2 = 0.6439$) and the initial output (Experiment no.1) has a speed rate of 1400 rpm, a thickness of 1.5 g/m, and a slidver gap of 20 cm.

Table 6. Experiment matrix with multi-response

Exp. no.	Speed rate (rpm)	Thickness (g/m)	Slidver gap (cm)	CC	Q	Desirability
1	1400	1.5	20	0.6007	0.7296	0.9560
2	1500	1.3	30	0.4879	0.5730	0.3504
3	1300	1.4	20	0.3128	0.6125	0.3070
4	1300	1.3	30	0.2787	0.5365	0.0000
5	1400	1.4	30	0.3211	0.5976	0.2862
6	1500	1.5	30	0.3338	0.7118	0.5119
7	1400	1.4	30	0.3155	0.5706	0.2083
8	1300	1.5	30	0.3358	0.7478	0.5665
9	1400	1.4	30	0.3209	0.5966	0.2836
10	1400	1.3	40	0.3194	0.5978	0.2845
11	1500	1.4	20	0.2106	0.5388	0.0000
12	1500	1.4	40	0.3377	0.7024	0.5058
13	1400	1.3	20	0.3192	0.5943	0.2760
14	1400	1.4	30	0.3101	0.5529	0.1407
15	1400	1.4	30	0.3079	0.5453	0.1019
16	1400	1.5	40	0.3288	0.6344	0.3747
17	1300	1.4	40	0.2117	0.5587	0.0172

Sensitivity analysis is a research method that evaluates the impact of changes in the input data used in MCDM models. It is a widely used method to ensure the robustness and stability of solutions. The sensitivity analysis was utilized to ascertain variation of criteria weights. The weight adjustment method is applied across nine sets to examine the impact of different weight distributions on the criteria. The set of criteria weights are explained in Table 7.

This paper presents a comprehensive two-phase sensitivity analysis process. In the first phase, a weight adjustment method is applied across the nine sets the impact of different weight distributions on the criteria. Using the same calculation methodologies as in Set 5, the desirability for all sets is displayed in Table 8, and the weights are ranked in Figure 6.

Table 7. The distribution weights

Set of criteria weights	Response	
	Defect (% weights)	Downtime (% weights)
1	10	90
2	20	80
3	30	70
4	40	60
5	50	50
6	60	40
7	70	30
8	80	20
9	90	10

Table 8. The desirability for nine sets of criteria weights

Exp.no	Desirability								
	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
1	0.9690	0.9819	1.0000	1.0000	0.9560	0.7863	0.6438	0.4098	0.3261
2	0.6437	0.6345	0.6019	0.5260	0.3504	0.2178	0.1893	0.1108	0.1088
3	0.2704	0.2808	0.2779	0.3050	0.3070	0.3208	0.4826	0.4946	0.4887
4	0.1994	0.1861	0.1536	0.1211	0.0000	0.0889	0.3083	0.2842	0.3187
5	0.5041	0.4919	0.4493	0.4120	0.2862	0.1336	0.1848	0.0592	0.0623
6	0.2895	0.3261	0.3544	0.4352	0.5119	0.5926	0.8653	0.8345	0.8024
7	0.4536	0.4384	0.3928	0.3469	0.2083	0.0827	0.0000	0.0510	0.0658
8	0.2716	0.3185	0.3580	0.4587	0.5665	0.6900	1.0000	1.0000	1.0000
9	0.4991	0.4871	0.4450	0.4082	0.2836	0.1339	0.1629	0.0632	0.0673
10	0.5383	0.5233	0.6292	0.4295	0.2845	0.1041	0.0632	0.0038	0.0023
11	0.0143	0.0000	0.0000	0.0000	0.0000	0.0000	0.4095	0.4371	0.4653
12	0.6004	0.6039	0.5806	0.5818	0.5058	0.3359	0.3968	0.2125	0.1851
13	0.5391	0.5228	0.4732	0.4250	0.2760	0.0954	0.0000	0.0000	0.0000
14	0.4016	0.3850	0.3389	0.2886	0.1407	0.0512	0.0993	0.0688	0.0946
15	0.3914	0.3730	0.3246	0.2687	0.1019	0.0000	0.0566	0.0579	0.0868
16	0.3779	0.3864	0.3776	0.3962	0.3747	0.3357	0.4963	0.4125	0.4013
17	0.0000	0.0000	0.1111	0.0000	0.0172	0.1153	0.4973	0.5243	0.5399

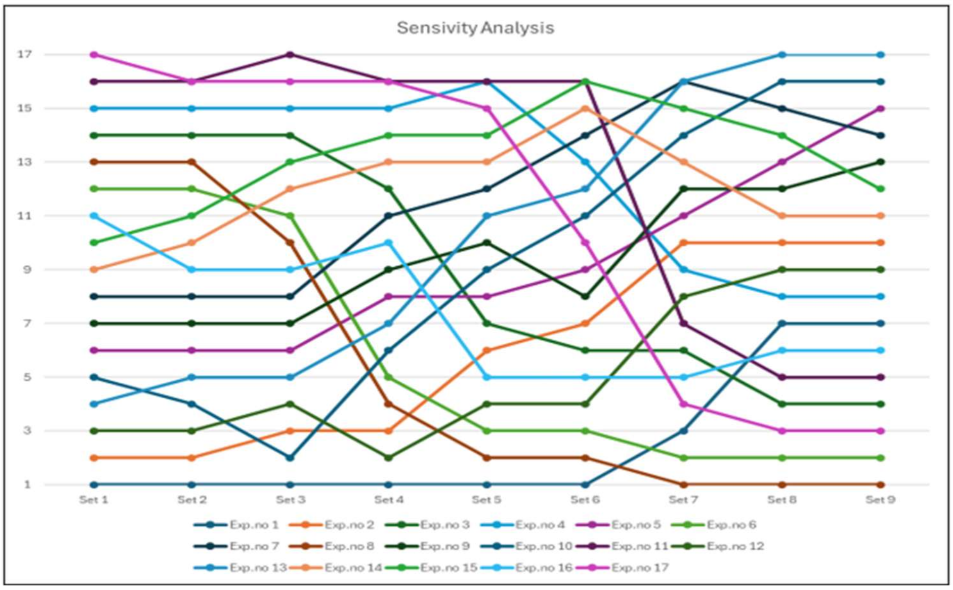


Fig. 6. The sensitivity analysis of criteria weights

Subsequently, the efficiency values of all scenarios are utilized to calculate the optimal parameters and predicted results for each case, using Design Expert V13. As a result, Table 9 presents the optimal parameters with the predicted responses of alternatives throughout nine sets.

Table 9. A comprehensive comparison of the optimal parameters

Set of criteria weights	Initial output	Optimal parameters	Predict results	
			Defect (kg)	Downtime (min)
Set 1	$A_2B_3C_1$	$A_1B_3C_1$	2.54	360.67
Set 2	$A_2B_3C_1$	$A_1B_3C_1$	2.54	360.67
Set 3	$A_2B_3C_1$	$A_1B_3C_1$	2.54	360.67
Set 4	$A_2B_3C_1$	$A_1B_3C_1$	2.54	360.67
Set 5	$A_2B_3C_1$	$A_1B_3C_1$	2.54	360.67
Set 6	$A_2B_3C_1$	$A_1B_3C_1$	2.54	360.67
Set 7	$A_1B_3C_2$	$A_1B_3C_1$	2.54	360.67
Set 8	$A_1B_3C_2$	$A_1B_3C_1$	2.54	360.67
Set 9	$A_1B_3C_2$	$A_1B_3C_1$	2.54	360.67

Table 9 presents that despite the weights fluctuating, the optimal parameters are similar ($A_1B_3C_1$), while an optimization strategy focuses on the minimum defect and downtime to achieve. The predicted defects weighed 2.54 kg, and the downtime was 360.67 mins. The optimal parameters identified are a speed rate of 1300 rpm, a thickness of 1.5 g/m, and a slidver gap of 20 cm. These adjusted settings can increase productivity enhancement efficiency.

In addition, we compared the suggested strategy to other established techniques such as ARAS, COPRAS, and MOORA, which are displayed in Table 10. The data analysis was conducted using the hybrid MCDM approach with weights set to $w_{defect} = 0.50$ and $w_{downtime} = 0.50$ with a simpler calculating technique, it produces similar findings to well-known methods. This means it may be applied to a wider range of MRO (Saeed et al., 2024), particularly those involving large amounts of data, demonstrating the suggested solution's effectiveness and robustness.

Table 10. Comparison of the hybrid MCDM method and the other methods

Method	Optimal parameters
1. ARAS	$A_1B_3C_1$
2. COPRAS	$A_1B_3C_1$
3. MOORA	$A_1B_3C_1$
4. Proposed	$A_1B_3C_1$

The analysis in Table 10 demonstrates that the best values found are similar across most MCDM approaches ($A_1B_3C_1$). The consistent results shown here confirm the robustness and stability of these approaches in optimizing the cotton swab procedure's parameters. The consistent outcomes obtained from various MCDM methods indicate that these parameters are appropriate for attaining the intended performance metrics.

3.5 Energy Analysis

Analyzing the data on the plant's total energy consumption provides significant information about the energy sources that are accessible in Table 11 and 12, which have statistics on the energy intake for each of the unit operations (Waheed et al., 2008). The sensitivities of the equipment used in the experiment were calculated based on the data supplied in Table 13.

Table 14 presents the total energy demands for the eight specified unit processes, measured by time and energy consumption. In this case study, the energy consumption of cotton was determined to be 6,208.08 MJ. Electric, thermal, and manual energy categories account for 43.12%, 55.73%, and 1.15% of the total energy consumption, respectively. The table unambiguously demonstrates that the drying process was the most energy-intensive, accounting for roughly 69.93% of the total energy input. The packaging

Table 11. Specifications pertaining to the operation of generators, boilers, and cotton

Generators operating conditions	Value
Power factor (PF)	0.8
KVA	437.5
KW	350
Load during production	95%
Diesel usage (l/h)	60
Boiler operating conditions	Value
Thermal capacity (kW)	3200
Heat Input (kW)	3406
Diesel usage (l/h)	35
Operating temperature (°C)	107
Operating pressure (bar)	8
Cotton operating conditions	Value
Mass flow rate of cotton (kg/h)	1200
Heat capacity of cotton (kJ/kg.K.)	4.06
Heat capacity of water (kJ/kg.K.)	4.15

Table 12. Factors for evaluating energy consumption in cotton manufacturing

Unit	Operation Required parameters	Value
Chemical process	Number of persons involved in chemical process	4
	Time taken for chemical process (h)	5
Fiber carding	Electrical power (kW)	4.28
	Number of persons involved in fiber carding	12
	Time taken for fiber carding (h)	5
Slidver	Electrical power (kW)	4.63
	Number of persons involved in slidver	4
	Time taken for slidver (h)	6
Plastic injection	Electrical power (kW)	15.12
	Number of persons involved in plastic injection	5
	Time taken for plastic injection (h)	6
Plastic rods	Electrical power (kW)	16.64
	Number of persons involved in plastic rods	4
	Time taken for plastic rods (h)	5
Swab machine	Electrical power (kW)	18.37
	Number of persons involved in swab machine	4
	Time taken for swab machine (h)	6
Drying	Electrical power (kW)	50.46
	Number of persons involved in drying	6
	Time taken for drying (h)	6
	Steam mass requirement (kg/h)	3200
	Weight fraction of water in cotton	0.96
	Steam inlet temperature (K)	360
	Temperature of surrounding (K)	300
	Cotton inlet temperature (K)	325
	Cotton outlet temperature (K)	353
	Thickness of cotton (g/m)	1.01
Packaging	Electrical power (kW)	58.68
	Time taken for packaging (h)	5
	Number of persons involved in packaging	10

Table 13. Equipment utilized in the inquiry and sensitivities

Equipment	Precision maintenance (%)	Accuracy maintenance (%)	Error maintenance (%)
Tachometer	0.01	0.02	0.02-0.04
Stopwatch	0.02	0.03	0.03-0.07
Weighting balance	0.03	0.05	0.05-0.10
Thermocouples	0.05	0.01	0.01-0.10

unit followed, accounting for 13.83% of the total energy.

Together, both units contribute 83.76% of the total energy. The chemical process unit used the least amount of energy, accounting for approximately 0.09% of the total energy input. The type of operation dictates the fluctuation in energy consumption for each unit activity, together with other operational factors such as equipment age and the extent of plant capacity utilization.

Exergy analysis has been used to assess the unit processes integrated in cotton production, thereby analyzing the entire production. Table 15 displays the exergy change in cotton, the useful work, the utility exergy change, the generation of entropy, and the inefficiency linked to each individual unit activity. The variation in the cotton exergy is only linked to processes in which there is a modification in the temperatures via which the product enters and exits. Hence, there is a generation of exergy during the drying and packaging processes. Chemical process, fiber carding, slidver, plastic injection, and swab machine activities do not exhibit any exergy change due to the absence of significant temperature variation between the entrance and output of these processes. The negative exergy change observed during packaging can be attributed to the decrease in temperature of the product during the procedure. The exergy of the coolant used to cool the processed material after drying was disregarded due to its negligible impact.

Useful work input includes both electrical and physical energy. The reason for including electrical energy in the

Table 14. The production of cotton requires the allocation of time and energy

No	Unit	Operation time (h)	Electrical energy $E_{p,i}$ (MJ)	Thermal energy $E_{t,i}$ (MJ)	Manual energy $E_{m,i}$ (MJ)	Total energy $E_{seo,i}$ (MJ)	$(E_{seo,i}/E_{tt})$ x100(%)
1	Chemical process	5.00	-	-	5.40	5.40	0.09
2	Fiber carding	5.00	61.63	-	16.20	77.83	1.25
3	Slidver	6.00	80.01	-	6.48	86.49	1.39
4	Plastic injection	6.00	261.27	-	8.10	269.37	4.34
5	Plastic rods	5.00	239.62	-	5.40	245.02	3.95
6	Swab machine	6.00	317.43	-	6.48	323.91	5.22
7	Drying	6.00	871.95	3,459.90	9.72	4,341.57	69.93
8	Packaging	5.00	844.99	-	13.50	858.49	13.83
	Total		$E_{p,tt}$	$E_{t,tt}$	$E_{m,tt}$	E_{tt}	100.00
			2,676.90	3,459.90	71.28	6,208.08	
	Percent (%)		43.12	55.73	1.15	100.00	

Table 15. Exergy balance in cotton processing

No	Unit	Exergy change of the cotton (MJ)	Useful work (MJ)	Utilities exergy change (MJ)	Production of entropy (MJ)	Inefficiency (%)
1	Chemical process	-	5.40	-	5.40	0.02
2	Fiber carding	-	77.83	-	77.83	0.34
3	Slidver	-	86.49	-	86.49	0.38
4	Plastic injection	-	269.37	-	269.37	1.18
5	Plastic rods	-	245.02	-	245.02	1.07
6	Swab machine	-	323.91	-	323.91	1.42
7	Drying	779.80	871.95	20,759.40	20,851.55	91.24
8	Packaging	-148.30	844.99	-	993.29	4.35
	Total	631.50	2,719.56	20,759.40	22,852.86	100.00

assessment of beneficial work is due to its composition of pure exergy, which cannot be fully accounted for by the entropy produced by a human laborer. The entropy reached its maximum value in the drying unit, followed by the packaging unit, with values of 20, 851.55 and 993.29 MJ, respectively. In the drying and packaging unit, the respective inefficiencies are 91.24% and 4.35%, whereas the combined inefficiencies in the other five units amount to a mere 4.41%. The observed high entropy during the drying process can be attributed to the irreversibility resulting from the significant temperature differential between the inlet and outflow streams of the product. These data demonstrate that the heating process is extremely inefficient. Exergy calculations consistently illustrate this phenomenon, as the exergy value of heat is frequently far lower than its energy value, especially at temperatures near the reference temperature (Arshad et al., 2019). An elevated level of exergy destruction indicates that the energy has diminished in its capacity to generate work, leading to a decline in its quality.

The exergy degradation during drying can be mitigated by increasing the capacity of the holding tank, therefore reducing the strain on the boiler (Zhang et al., 2018). This will facilitate an extended duration of production, hence minimizing unnecessary energy consumption and the concurrent exergy degradation resulting from plant initiation, shutdown, and cleaning. Implementing this proposal could potentially enable the refinery to decrease its substantial energy costs, therefore enhancing profitability.

3.6 Validation and Confirmation

This confirms that the practical findings are equally as good as the results achieved through experiments. During the trial, the researcher applied the factors discussed in the previous article.

In Table 16, shows that the trial yielded a total of 10 practical responses. The researcher utilized statistical analysis by one sample t-test (Yu et al., 2022) with defect and downtime. Meanwhile, the responses from the actual application agree with those obtained from the predicted ($p > 0.05$), as shown in Fig. 7.

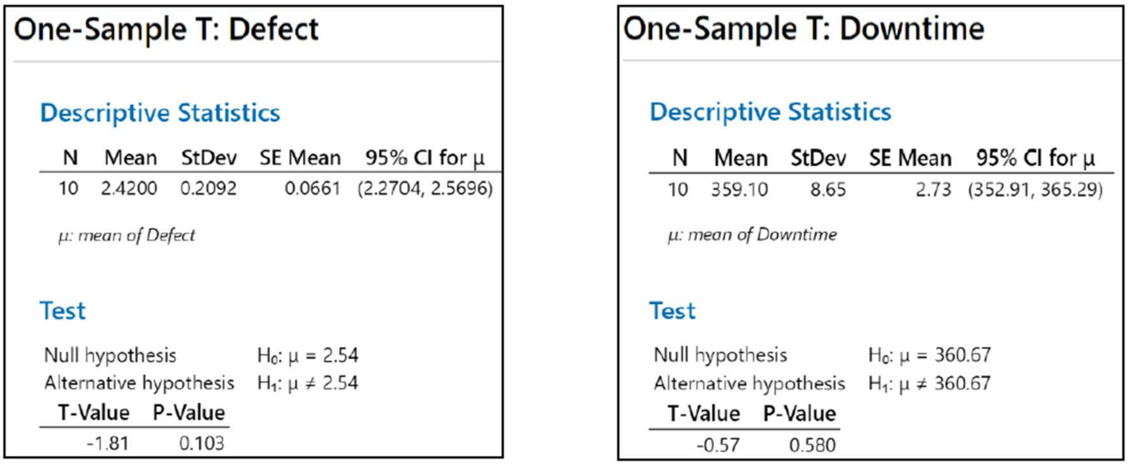
The optimal conditions of the proposed method were compared to the initial output of condition A (set 1-5; Exp.no 1) and condition B (set 6-8; Exp.no 8) for confirmation. Fig. 8 illustrates that only specific approaches provided the most appropriate outcomes when considering both the suggested approach and the current parameters for each response. In Table 17, the cost analysis should solve multiple responses and eliminate the differences between each perspective (Shabbir et al., 2020). That can be calculated with each response as follows:

(1) The cost of defects includes labour, raw materials, packaging, and management. As a result, the cost per kilogram is $30.49 overall.

(2) The downtime costs include labor costs, breakdown costs, and management costs, resulting in a total cost of $0.06 per min.

Table 16. The result of actual practical

Run	Speed rate (rpm)	Thickness (g/m)	Slidver gap (cm)	Defect	Downtime
1	1300	1.5	20	2.46	355
2				2.06	342
3				2.33	349
4				2.74	365
5				2.55	362
6				2.39	365
7				2.12	370
8				2.61	358
9				2.43	367
10				2.51	358


One-Sample T: Defect

Descriptive Statistics

N	Mean	StDev	SE Mean	95% CI for μ
10	2.4200	0.2092	0.0661	(2.2704, 2.5696)

μ: mean of Defect

Test

Null hypothesis H₀: μ = 2.54

Alternative hypothesis H₁: μ ≠ 2.54

T-Value	P-Value
-1.81	0.103

One-Sample T: Downtime

Descriptive Statistics

N	Mean	StDev	SE Mean	95% CI for μ
10	359.10	8.65	2.73	(352.91, 365.29)

μ: mean of Downtime

Test

Null hypothesis H_0: μ = 360.67

Alternative hypothesis H_1: μ ≠ 360.67

T-Value	P-Value
-0.57	0.580

(a) (b)

Fig. 7. Confirmation with the T-test of (a) the defect, and (b) the downtime

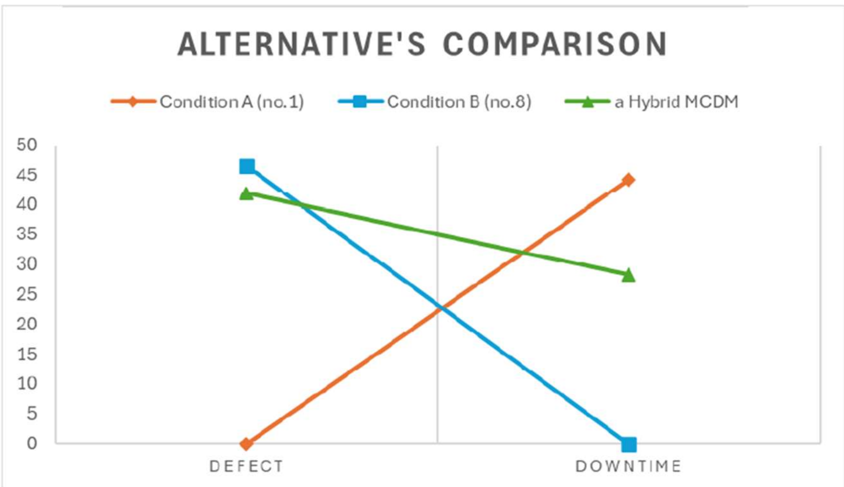


Fig. 8. The alternative of comparison

Table 17. The losses costs matrix for each response

Cost	Defect costs (kg)	Downtime costs (min)
1. Labor cost (dollars/month)	500	500
2. Electricity cost (dollars/month)	55.56	-
3. Depreciation cost of machinery (dollars/month) A = P (A/P, i%, N)	98.86 (8.333, n=10, i=5%)	-
4. Breakdown cost (spare part and avg. downtime is 400 min/month)	-	26.25
5. Raw material and packaging cost (dollars/month)	2,500	-
6. Management cost (dollars/month)	200	50
7. Total cost (dollars/month)	3,354.42	576.25
8. Cost per unit (dollars)	30.49	0.06

According to the data presented in Table 18, a hybrid MCDM approach demonstrates a reduction in cost from a condition A and condition B of 33.86% and 2.45%, respectively. Therefore, operators responsible for cotton swab manufacture should select a speed rate of 1300 rpm, a 1.5 g/m thickness, and a sliding gap of 20 cm. This option is the most appropriate for present operations.

Table 18. Comparison of proposed and present methods for cotton juice process parameter optimization

Method	Optimal parameters	(1) Defect costs	(2) Downtime costs	Total cost (1) + (2)	Improvement (%)
1. Condition A (exp.no.1)	$A_2B_3C_1$	131.11	16.80	146.91	33.86
2. Condition B (exp.no.8)	$A_1B_3C_2$	70.13	30.12	100.25	2.45
3. Hybrid method	$A_1B_3C_1$	76.23	21.60	97.83	-

3.7 Discussion of Findings

This research shows that the hybrid MCDM approach is highly efficient in dealing with complicated decision-making situations such as robot selection (Goswami et al., 2021), university selection (Miç and Antmen, 2021), Fish Scale Scraping Machine (Sriburum et al., 2023), and the lightweight concrete block process (To-On et al., 2023). This indicates that the combination of these methods can lead to better decision-making outcomes compared to traditional signal criteria approaches. The proposed method's R^2 and adj R2 were higher than those of TOPSIS and WASPAS indicating a higher prediction accuracy.

The findings emphasize the importance of sensitivity analysis in the decision-making process. By evaluating how changes in criteria weights or input data affect outcomes, despite the weights fluctuating, the optimal parameters are similar. It shows that the model is insensitive to weights and maintains stability. Meanwhile, this comparison with other existing optimization methods includes ARAS, COPRAS, and MOORA. The optimal parameter was found to be $A_1B_3C_1$, indicating the robustness and reliability of these methods in optimizing the cotton swab process. Consequently, the hybrid methods allow for a more comprehensive evaluation of multiple conflicting criteria, leading to better-informed decisions. This is particularly useful in complex manufacturing environments where trade-offs between cost, quality, and efficiency must be carefully managed.

4. CONCLUSION

The hybrid MCDM approach is utilized to optimize parameters in cotton swab manufacturing. The paper discusses the use of response surface plots to analyse the relevant factors for defects and downtime. Furthermore, the study utilizes TOPSIS with linear programming and WASPAS to normalize criteria and determine ideal points for decision-making. The optimal conditions were a speed rate of 1300 rpm, a thickness of 1.5 g/m, and a slidver gap of 20 cm. The predicted defects and downtimes were 2.54 kg and 360.67 mins, respectively. Validation and confirmation of the proposed method are critical, as demonstrated by one sample t-test. The actual practical and predicted values were not significantly different ($p > 0.05$). The energy consumption of cotton was determined to be 9,681.33 MJ. Electric energy, thermal energy, and manual energy account for 18.36%, 81.29%, and 0.35% of the total energy consumption, respectively. The drying process was the most energy-intensive component, accounting for approximately 69.93% of the total energy consumption. The chemical process unit used a small amount of energy, accounting for approximately 0.09% of overall energy consumption. The entropy reached its maximum value in the drying unit and packaging unit, with values of 20,851.55 and 993.29 MJ, respectively. The drying and packaging units have inefficiencies of 91.24% and 4.35%, respectively, while the combined inefficiencies in the other five units are only 4.41%.

The hybrid method provides a comprehensive evaluation of alternatives, identifies optimal solutions, which is particularly useful in production contexts with conflicting objectives. That can be applied and practical in numerous sectors, including manufacturing, healthcare, agriculture, and supply chain management, to improve processes and decision-making strategies. Meanwhile, MCDM methods' limitations focus on quantitative criteria; they may overlook qualitative factors that are difficult to measure but still important in decision-making. This can lead to an incomplete assessment of alternatives and potentially suboptimal decisions and integration of multiple methodologies can increase implementation complexity. Practitioners may require advanced knowledge and skills to effectively apply the hybrid approach, which could be a barrier for smaller organizations or those with limited expertise.

Furthermore, given the valuable insights and discoveries, there are numerous potential avenues for further investigation and advancement.

1. Exploring advanced mathematical models, machine learning techniques, and artificial intelligence technologies may increase decision-making efficiency. Meanwhile, investigating multi-objective optimization techniques to simultaneously optimize multiple conflicting objectives, such as cost, quality, and sustainability, could be an exciting direction for future work. This could involve developing decision-making frameworks that consider trade-offs between different performance metrics.
2. We can extend the hybrid MCDM approach to optimize the entire supply chain of manufacturing or another field. This could include factoring in supplier selection, inventory management, and distribution logistics in the decision-making process.
3. An assessment of the plant's total energy usage yields crucial data regarding the quantity of energy that is available. The aggregate energy consumption encompasses electrical, thermal, and manual energy. Conduct an analysis of energy usage in unit operations to study the pattern of energy distribution and consumption. For the sake of sustainability, the research has prioritized improving efficiency, minimizing manufacturing costs, and tackling environmental issues associated with energy use in production.

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests.

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