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The Application of Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS Multicriteria Methods to Optimize Downtime in a Production Process

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A B S T R A C T

In the industrial transformation of animal feed for chickens, downtime analysis is a crucial part of the plant's operations. Unfortunately, the literature on downtime analysis has a serious shortcoming; it fails to link downtime with Taguchi method's optimization and ranking. To correct this deficiency, this paper proposes a new method that couples the Taguchi scheme with the weighted sum method (WSM), weighted product method (WPM) and weighted aggregated sum product assessment (WASPAS) method. A new model was developed to contain downtime factors, levels, orthogonal matrix, signal-to-noise proportions, normalisation indices, criteria weights and preference scores. The results of the Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS show that workstation 2 has the highest rankings of 0.8446, 8.9090 and 4.8770 for the Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS, respectively. Also, the lowest rankings of 0.1553, 6.7990 and 3.4800 were recorded for workstation 1 using the Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS methods, respectively. However, from literature reports, WASPAS has been associated with the best results compared to WSM and WPM. Hence, from the various results of prioritizing workstations 1 and 2, the results of the Taguchi-WASPAS method are recommended. This is the first time the downtime problem for animal feed processing equipment will be approached by a joint optimization and ranking with the Taguchi scheme, WSM, WPM and WASPAS multicriteria methods.

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1. INTRODUCTION

The territory of the Republic of Indonesia covers an area of 1905 million km^2 and has a population of 2706 million according to World Banks statistics in 2019. Indonesia belongs to Southeast Asia and Oceanic, lying between the Indian and Pacific oceans. The position of Indonesia regarding the consumption of broiler gives abundant opportunity for the development of the animal feed industry in the country (Zahari and Wong, 2009; Haryo et al., 2017; Parmawati et al., 2018). The research on broiler/animal feed has evolved significantly (Manning et al., 2007; Balogun et al., 2013; Chehraghi et al., 2013; Salawu et al., 2014; Donma and Donma 2017). This phenomenon has been studied across several geographical domains such as the UK (Manning et al., 2007), Turkey (Donma and Donma, 2017), Iran (Chehraghi et al., 2013) and Nigeria (Balogun et al., 2013; Salawu et al., 2014). Interestingly, in the recent past, the Ministry of Agriculture in Indonesia declared a growing trend in the 2014 to 2017 values of consumption of broiler/broiler meat per capita (Rahmawan et al.,2020). This was followed by a growth in the requirement for animal feed for chickens according to Rahmawan et al. (2020). A previous study (Rahmawan et al., 2020) indicated the urgency to study the process variables in the animal feed processing industries.

In the companies that offer huge amounts of animal feed for chickens in Indonesia, the process variables have changed (Riduwan and Prasetyo, 2020). The machines are ageing and there is a continuous difficulty of replacing parts just-in-time due to logistics inefficiency and the economic downturn in the country. The problem is compounded by the high labour turnover from the agricultural industry to manufacturing and extractive industries that offer higher wages to the workers (Riduwan and Prasetyo, 2020). Consequently, there is a need to have a clear way of optimizing the downtime parameters in the animal feed processing industry and rank the important parameters according to the priorities that should be given to them. This will provide information on how to enhance the plant's capacity and throughput of the system (Adusei-Bonsu et al., 2021; Pezo et al., 2021). It will also aid in providing timely delivery of animal feed to customers and enhance the goodwill of the company. The plant may plan on expansion or lean activities due to customer demands and the dwindling economy and there is no way of easily evaluating the optimum downtime of the plant to meet up with the anticipated changes in the plant's capacity and delivery levels. Sharing this information with the board of directors is difficult as no concrete facts are available to the manager of the plant. The problem described above resembles that of the case study presented in Rahmawan et al. (2020).

However previous studies are principally dedicated to the meat consumption characteristics (e.g. Donma and Donma, 2017; Salawu et al., 2014) with an exception (Rahmawan et al.,2020). Still, downtime analysis is not completely understood and signifies a clear gap in the process performance/ broiler/animal feed literature. Oji and Oke (2020) proposed the Taguchi scheme, Taguchi-Pareto-and Taguchi ABC to solve the downtime problem in the maintenance system of a bottling plant. Subsequently, other scholars (Okanminiwei and Oke, 2020) have researched the Taguchi scheme, Taguchi-Pareto and Taguchi-ABC and applied the models to a container terminal in a developing country. Considering that downtime is associated with machine failures, some authors (Inyiama and Oke, 2020) have analysed the maintenance downtime problem by deploying the Weibull failure distribution function. Some scholars considered the fusion of Poisson distribution with the Taguchi method and determined the optimization model for a process plant (Raji and Oke, 2019). By considering the plastic industry, some scholars instituted a deterministic framework for downtime analysis and analysed it with an example (Nwanya et al., 2017). However, the above studies on maintenance downtime still exhibit some problems.

Primarily is the ranking problem which has not been extensively analysed in the animal feed processing literature; there appears that no study has focused on the optimization of maintenance downtime despite the urgency of attention needed in this research domain (Adusei-Bonsu et al., 2021; Pezo et al., 2021). Even in the manufacturing literature, the ranking produced by the delta mechanism of the Taguchi scheme, through reliable, has been argued to need improvement. Proponents are of the idea that the combination of models produces better results than single models as the synergic advantages of the component models produce a framework that addresses the weaknesses of the component models. It is believed that the integration of multicriteria models of weighted sum model, weighted product model and weighted aggregated product assessment model will add value to the enhancement of downtime measurement and improvement effort of the animal feed processing system. Based on the above reason, in the proposed framework, the WPM, WSM and WASPAS methods are integrated with the Taguchi scheme, which is first applied to the downtime data.

In this study, an attempt is made to contribute to closing this knowledge gap in the literature. The work responds to the frequent calls for more studies on the performance enhancement of the animal feed production system. This paper aims to analyse the downtime process parameters in an animal feed engineered system, develop optimal parametric values for process optimization using the Taguchi method, and concurrently ranks the parameters according to importance. Process optimization could occur at different facets of the system. However, the work specifically focuses on two principal workstations in the case study organisation in the packaging process that reveals numerous causes of downtime. It treats these workstations as levels in the factors-level analysis of the Taguchi scheme and then introduced the orthogonal array to initiate the computation of the signal-to-noise level, which will result in the response table development and the eventual establishment of the optimal parametric values, which became input into the multicriteria analysis. The outcome of the Taguchi scheme is used as the weight of the weighted sum method and the weighted product method in multicriteria analysis.

To sum up, the contribution of this paper is to highlight the evaluation parameters of the downtime and attributes yet unclear in previous downtime research, which may enhance an understanding of researchers on the evaluation parameters. Secondly, it implements a Taguchi scheme method with an integration of the weighted sum method multicriteria analysis that potentially produces new reasoning and improves the current concept in evaluating downtime for an animal feed system. Thirdly, it establishes research flaws on downtime analysis to adequately locate new research endeavors.

2. METHODS

2.1 The concept of weighted sum model (WSM)

Alternatively known as the simple additive weighting (SAW) or the weighted linear combination (WLC), the weighted sum method (WSM) is popularly adopted in decision making as it exhibits simplicity in assessing multiple options with dependable results. The idea of weight average is that the average values of the elements of the decision matrix representing each factor under the two separate workstations I and II are obtained. These are then multiplied such that each decision matrix element is multiplied by a weight. The results are thereafter added. However, care is taken about the properties being evaluated to be comparable across the attributes units. This prompts the adoption of normalization of the factors since the attributes being added are of different units. In other instances compensation between the attributes is considered where the attributes are evaluated proportionately to the quotients of their weights.

From the literature search, there have been divergent views about the name given to the method as some propose the name, additive aggregation model, instead of WSM. Furthermore, the idea of weights, which is a common term used to describe the important feature of the WSM has been challenged to be replaced with another term, scaling constants. The argument to support this proposal is that they function to establish a rate of compensation between factors as opposed to the prioritization of the importance of the factors. Furthermore, the decision criteria are the backbone of the WSM. In criteria development for the WSM, comparative weights are mapped to each criterion by judging how important the workstation criteria are to in the circumstance. The literature provides two alternative routes of weight assignments to criteria. In an instance, a maximum mark of say 10 may be shared among the alternative criteria by a team while the aggregate of the marks considered and an average adopted as the accepted criterion weight.

However, the second route, adopted is to use a predefined value based on a previous computation. In this article, the Taguchi method was first deployed to evaluate the criteria and the aspect ratio of the individual delta values to the total delta value was established. Thus, by evolving a weighted decision matrix, the researchers have a tool to compare the factors within each of the workstations in the context of multiple factors of varying degrees of importance to the achievement of the downtime reduction goal. The utilized decision matrix while limiting subjectivity in decision-making assists in attaining and enhanced clarity and objective decisions. By using the WSM, all the diverse multi attributes are integrated into a scalar framework for decision making.

The weighted sum method is initiated with the ideas in Equations (1) and (2). Equation (1) is for beneficial characteristics and Equation (2) is for non-beneficial characteristics (Onajite and Oke, 2021):

Beneficial attributes: $X = x/x_{max}$ (1)
Non-beneficial attributes: $X = x_{min}/x$ (2)

wherex_{min} and x_{max} represent the minimum and maximum values of the data, and the set in the group considered and X is the estimated value. Now, the values obtained in Equations (1) and (2) are substituted as weights in Equation (3) (Onajite and Oke, 2021).

$$A_i^{WSM-score} = \sum_{j=1}^{n} w_i a_{ij} \text{, for } i=1,2,3,\ldots,m \quad (3)$$

wherew_i illustrates the comparative weight of importance of the interior C_j while a_{ij} represents the performance value (normalized scale) of option A_i while it is appraised regarding criterion C_j. It follows that the total (as all criteria are treated concurrently) significance of option A_i, is denoted as $A_i^{WSM-score}$.

The steps involved in WSM are described below (Onajite and Oke, 2021):

Step 1: The decision criteria can be established in matrix format as

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdot & p_{1n} \\ p_{21} & p_{21} & \cdot & p_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ p_{m1} & p_{m2} & \cdot & p_{mn} \end{bmatrix} \quad (4)$$

Step 2: The value in the decision matrix are normalized based on their type of criteria p_{ij} as (Onajite and Oke, 2021):

(a) For a beneficial criterion

$$p_{ij}^{'} = \frac{p_{ij}}{p_{ij}^{\max}} \quad (5)$$

(b) For a non-beneficial criterion

$$p_{ij}^{'} = \frac{p_{ij}^{\min}}{p_{ij}} \quad (6)$$

$$P^{'} = \begin{bmatrix} p_{11}^{'} & p_{12} & \cdot & p_{1n}^{'} \\ p_{21} & p_{21} & \cdot & p_{2n}^{'} \\ \cdot & \cdot & \cdot & \cdot \\ p_{m1}^{'} & p_{m2}^{'} & \cdot & p_{mn}^{'} \end{bmatrix} \quad (7)$$

Step 3: The weight normalized decision matrix (Onajite and Oke, 2021)

$$Y = W_j p_{ij}^{'} \quad (8)$$

But Y is given as

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdot & y_{1n} \\ y_{21} & y_{21} & \cdot & y_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ y_{m1} & y_{m2} & \cdot & y_{mn} \end{bmatrix} \quad (9)$$

Step 4: Preference score and ranking estimation (Onajite and Oke, 2021)

The preference score for WSM is derived by summing the matrix across rows.

$$A_i^{WSM} = \sum_{i=1}^{m}\sum_{j=1}^{n} W_{ij} p_{ij} \tag{10}$$

Each alternative will give a preference score with which they are ranked. The alternative with the highest preference score is ranked 1 and the ranking goes in ascending orders.

Step 5: Result (Onajite and Oke, 2021)
The alternative with the highest rank is selected as the best alternative and the next ranked alternative can be selected in the absence of the highest-ranking alternative.

2.2 The concept of WPM (Onajite and Oke, 2021)

The weighted product model (WPM) is a multicriteria decision-making method that is used to select the best alternatives from a list. In this method, the preference score is derived by multiplying through the rows in the weighted normalized matrix.

The steps involved in WPM are as follows (Onajite and Oke, 2021):
Step 1: (Repeat of Equation (4)). The decision criteria can be established in matrix format as

$$P = \begin{bmatrix} p_{11} & p_{12} & \cdot & p_{1n} \\ p_{21} & p_{21} & \cdot & p_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ p_{m1} & p_{m2} & \cdot & p_{mn} \end{bmatrix}$$

Step 2: The value in the decision matrix are normalized based on the type of criterion p_{ij} as (Onajite and Oke, 2021)
(a) For a beneficial criterion

$$p_{ij}^{'} = \frac{p_{ij}}{p_{ij}^{\max}}$$

(b) For a non-beneficial criterion

$$p_{ij}^{'} = \frac{p_{ij}^{\min}}{p_{ij}}$$

$$P^{'} = \begin{bmatrix} p_{11}^{'} & p_{12} & \cdot & p_{1n}^{'} \\ p_{21} & p_{21} & \cdot & p_{2n}^{'} \\ \cdot & \cdot & \cdot & \cdot \\ p_{m1}^{'} & p_{m2}^{'} & \cdot & p_{mn}^{'} \end{bmatrix}$$

Step 3: The weight normalized decision matrix (Onajite and Oke, 2021)

$$Y = W_j p_{ij}^{'}$$

But Y is given as

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdot & y_{1n} \\ y_{21} & y_{21} & \cdot & y_{2n} \\ \cdot & \cdot & \cdot & \cdot \\ y_{m1} & y_{m2} & \cdot & y_{mn} \end{bmatrix}$$

Step 4: Estimate the preference score and ranking (Onajite and Oke, 2021)
The preference score for WPM is derived by multiplying the matrix across rows.

$$A_i^{WPM} = \prod_{j=1}^{n} p_{ij}^{W_j} \tag{11}$$

Step 5: Ranking (Onajite and Oke, 2021)
Each preference score will be ranked in ascending order with the highest value assigned a rank of 1
Step 6: Result (Onajite and Oke, 2021)
The alternative with the highest rank is selected as the best alternative and the next ranked alternative can be selected in the absence of the highest-ranking alternative.

2.3 The concept of WASPAS (Onajite and Oke, 2021)

The weighted aggregated sum product assessment is a unique combination of the weighted sum model (WSM) and weighted product model (WPM). This multicriteria decision-making method works in a way that smoothens the errors associated with WSM and WPM by making use of their preference scores values Q_i^1 and Q_i^2 respectively to get a joint generalized criterion of WASPAS using the formula (Onajite and Oke, 2021)

$$Q_i = \lambda Q_i^1 + (1-\lambda) Q_i^2 \tag{12}$$

where $\lambda = 0.5$

Ranking WASPAS (Onajite and Oke, 2021)
Q_i is ranked according to the highest values in the ascending order with the highest value ranked as the 1st position.

2.4 Procedure for data collection and analysis

The process of collecting and analyzing data followed in this article include the following steps:

Step 1: The main issue for collecting the secondary data is established. If downtime is found to be excessive at the packaging section of a production process, this suggests the need for control to improve the profit margin of the plant.

Step 2: The goal of the work is defined, which is to optimize the downtime considering two workstations in an animal feed production process by streamlining activities in the packaging section.

Step 3: The integrated Taguchi method with WSM, WPM and WASPAS is planned as the optimization and selection approach to solving the problem. These models are presented as Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS methods.

Step 4: Data is collected from the literature on the animal feed production industry.

Step 5: The obtained secondary data is analysed and interpreted.

Step 6: Suggestions for future research are made.

3. RESULTS AND DISCUSSION

3.1 Applying the Taguchi method to the data

The results in Table 1 are the original data provided by Rahmawan et al. (2020) that serve as the basis for computation in this paper. A novel approach was used to establish the levels for each workstation. Consider the present distribution of data for each of the two workstations. An attempt to extract levels from “Workstation 1” reveals that due to repetition, only six levels are possible, namely 16, 2, 22, 0, 1 and 10. However, when the "Workstation 2" is analysed for levels, ten levels are possible notably 11, 1, 22, 17, 7, 4, 5, 0, 2, 10. With differences in the level obtained from the analysis of the two workstations, the use of the conventional approach to level determination fails. Thus a new approach is necessary. This method works as follows. First, for each factor, the values at the different workstations are subtracted with the lower one removed from the higher value. The value is then assigned to the second workstation while the result, when divided by two is assigned to the first position. Consider the "replace pallet" factor, the difference between the values obtained in the two workstations is 5 and it is assigned as the value for workstation 2. This value is then divided by 2 to obtain 2.5, which is assigned to workstation 1. The same procedure is followed and the values in Table 2 are achieved.

Table 1. Activities that cause process downtime in minutes (Rahmawan et al., 2020)

Downtime causes (factors)	A	B	C	D	E	F	G	H	I	J
Workstation 1 (level 1)	16	2	22	0	1	0	2	1	0	10
Workstation 2 (level 2)	11	1	22	17	7	4	5	0	2	10

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

Table 2. Modified factor-level data based on Rahmawan et al. (2020)

Downtime causes (factors)	A	B	C	D	E	F	G	H	I	J
Workstation 1 (level 1)	2.5	0.5	0	8.5	3	2	1.5	0.5	1	0
Workstation 2 (level 2)	5	1	0	17	6	4	3	1	2	0

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

The structure of Table 2 is a 10–factor 2–level problem orientation from which the Minitab 18 software produces an L32 orthogonal array for the problem evaluation (Table 3). However, the entries in the orthogonal array are translated to actual values, Table 4.

Table 3. L32 orthogonal array for the downtime optimization problem

Expt. Trial	A	B	C	D	E	F	G	H	I	J
1	1	1	1	1	1	1	1	1	1	1
2	1	1	1	1	2	1	2	2	2	2
3	1	1	1	2	1	2	1	2	2	2
4	1	1	1	2	2	2	2	1	1	1
5	1	1	2	1	1	2	2	1	2	2
6	1	1	2	1	2	2	1	2	1	1
7	1	1	2	2	1	1	2	2	1	1
8	1	1	2	2	2	1	1	1	2	2
9	1	2	1	1	1	2	2	2	1	2
10	1	2	1	1	2	2	1	1	2	1
11	1	2	1	2	1	1	2	1	2	1
12	1	2	1	2	2	1	1	2	1	2
13	1	2	2	1	1	1	1	2	2	1
14	1	2	2	1	2	1	2	2	1	2
15	1	2	2	2	1	2	1	2	1	2
16	1	2	2	2	2	2	2	2	2	1
17	2	1	1	1	1	2	2	2	2	1
18	2	1	1	1	2	2	1	2	1	2
19	2	1	1	2	1	1	2	2	1	2
20	2	1	1	2	2	1	1	2	2	1
21	2	1	2	1	1	1	1	2	1	2
22	2	1	2	1	2	1	2	2	2	1
23	2	1	2	2	1	2	1	2	2	1
24	2	1	2	2	2	2	2	2	1	2
25	2	2	1	1	1	1	1	2	2	2
26	2	2	1	1	2	1	2	2	1	1
27	2	2	1	2	1	2	1	2	1	1
28	2	2	1	2	2	2	2	2	2	2
29	2	2	2	1	1	2	2	2	1	1
30	2	2	2	1	2	2	1	2	2	2
31	2	2	2	2	1	1	2	2	2	2
32	2	2	2	2	2	1	1	2	1	1

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

Table 4. Conversion of an orthogonal array into factor value

Expt. Trial	A	B	C	D	E	F	G	H	I	J	SN ratio*
1	2.5	0.5	0	8.5	3	2	1.5	0.5	1	0	-9.79
2	2.5	0.5	0	8.5	6	2	3	1	2	0	-11.23
3	2.5	0.5	0	17	3	4	1.5	1	2	0	-15.16
4	2.5	0.5	0	17	6	4	3	0.5	1	0	-15.54
5	2.5	0.5	0	8.5	3	4	3	0.5	2	0	-10.68
6	2.5	0.5	0	8.5	6	4	1.5	1	1	0	-11.30
7	2.5	0.5	0	17	3	2	3	1	1	0	-15.04
8	2.5	0.5	0	17	6	2	1.5	0.5	2	0	-15.34
9	2.5	1	0	8.5	3	4	3	1	1	0	-10.63
10	2.5	1	0	8.5	6	4	1.5	0.5	2	0	-11.40
11	2.5	1	0	17	3	2	3	0.5	2	0	-15.09
12	2.5	1	0	17	6	2	1.5	1	1	0	-15.32
13	2.5	1	0	8.5	3	2	1.5	1	2	0	-9.86
14	2.5	1	0	8.5	6	2	3	1	1	0	-10.85
15	2.5	1	0	17	3	4	1.5	1	1	0	-15.13

Table 4 (cont'd). Conversion of an orthogonal array into factor value

Expt. Trial	A	B	C	D	E	F	G	H	I	J	SN ratio*
16	2.5	1	0	17	6	4	3	1	2	0	-15.59
17	5	0.5	0	8.5	3	4	3	1	2	0	-11.35
18	5	0.5	0	8.5	6	4	1.5	1	1	0	-11.87
19	5	0.5	0	17	3	2	3	1	1	0	-15.29
20	5	0.5	0	17	6	2	1.5	1	2	0	-15.58
21	5	0.5	0	8.5	3	2	1.5	1	1	0	-10.60
22	5	0.5	0	8.5	6	2	3	1	2	0	-11.80
23	5	0.5	0	17	3	4	1.5	1	2	0	-15.40
24	5	0.5	0	17	6	4	3	1	1	0	-15.77
25	5	1	0	8.5	3	2	1.5	1	2	0	-10.73
26	5	1	0	8.5	6	2	3	1	1	0	-11.74
27	5	1	0	17	3	4	1.5	1	1	0	-15.37
28	5	1	0	17	6	4	3	1	2	0	-15.81
29	5	1	0	8.5	3	4	3	1	1	0	-11.28
30	5	1	0	8.5	6	4	1.5	1	2	0	-11.97
31	5	1	0	17	3	2	3	1	2	0	-15.34
32	5	1	0	17	6	2	1.5	1	1	0	-15.55

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor; *smaller-the-better

Next is the computation of the signal to noise ratio. A close examination of all the factors reveals that it is advisable to utilize the smaller-the-better criterion to evaluate the signal-to-noise ratio since the smaller values of all the factor downtime are desired. The applied formula is (Equation 13):

Smaller-the-better: $\eta = -10\log_{10}\frac{1}{n}\sum_{i=1}^{n} y_i^2$ (13)

where$n$ relates to the experimental trials conducted at the i^{th} experimental setting, y_i is the measure of the parameter being pursued in the work, η indicates the signal to noise.

Based on this, the computations of the signal-to-noise ratios are made, Table 4.

The values are then used to develop the response table, Table 5. Here, each factor and level is considered and references are made to the distributions in the orthogonal array and the averages are considered for the evaluation. In Table 5, factor "A" under level 1, the entry yields – 12.997. But how did we obtain this? The procedure starts with Table 3. Under factor "A" in Table 3, level 1, simply shown as "1" occurs in 16 places, starting from the experimental trial 1 and ending at experimental trial 16. The corresponding signal-to-noise ratios for each of these experimental trials are noticed as -9.79, -11.23, -15.16, -15.54, -10.68, -11.30, -15.04, -15.34, -10.63, -11.40, -15.09, -15.32, -9.86, -10.85, -15.13 and -15.59. The average of all these numbers from experimental trials 1 to 16 is -12.997. This is the value placed at the intersection of "A" and level 1 in Table 5. To complete the evaluation for the factor "A", Table 3 is referenced and all the level 2 items from experimental trials 17 to 32 are averaged regarding the signal-to-noise ratio to obtain -13.466 which is positioned in Table 5. Similar computations are made by using the data in Table 3 to obtain averages of the signal-to-noise ratio, which are then placed in Table 5, Next, the delta values, given as the difference between the values in levels 1 and 2 are obtained. This yields 0 as the maximum and -4.32 as the minimum for factors "B and J" as well as "D", respectively. Next, the ranks are obtained with factors "B" and "J" having the highest rank while factor "D" exhibits the lowest rank. The optimal parametric setting is then determined as the lowest values in either of the levels for factors "A" to "J". The optimal parametric setting is then $A_2B_1C_1D_2E_2F_2G_2H_2I_2J_2$, $A_2B_2C_1D_2E_2F_2G_2H_2I_2J_2$, $A_2B_1C_1D_2E_2F_2G_2H_2I_2J_1$ and $A_2B_2C_1D_2E_2F_2G_2H_2I_2J_1$.

3.2 Applying the Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS to the data

Furthermore, there is a need to connect the Taguchi method with the WSM, WPM and WASPAS. This motivated the current researchers to the proportion created by delta as the weighting factor. In this case, the value of delta for each factor is divided by the sum of all the delta values for the analysed factors. For instance, factor A has a delta value of -0.469 and the total is -6.399. Thus, the ratio for factor A becomes -0.469/-0.6399, which is 0.073. The weights for all the factors range from 0 to 0.675 with the highest occurring for factor D while the least values occurred for factors B and J.

Table 5. SN response table

Level	A	B	C	D	E
1	-12.9770	-13.2300	-13.2400	-11.0700	-12.9200
2	-13.4660	-13.2300	-13.2200	-15.3900	-13.5400
δ (delta)	-0.4690	0	-0.0200	-4.3200	-0.4700
Rank	6	1	2	9***	7
*I**	-13.466	-13.23	-13.22	-15.39	-13.5400
Input for a weighted average	$\frac{-0.469}{-6.399}$ = 0.0730	$\frac{0}{-6.399}$ = 0	$\frac{-0.02}{-6.399}$ = -0.0031	$\frac{-4.32}{-6.399}$ = 0.6750	$\frac{-0.47}{-6.399}$ = 0.0734
Level	F	G	H	I	J
1	-13.0700	-13.15	-12.9200	-13.1900	-13.2300
2	-13.3900	-13.25	-13.5400	-13.2700	-13.2300
δ (delta)	-0.3200	-0.1000	-0.6200	-0.0800	0
Rank	5	4	8	3	1****
*i**	-13.3900	-13.2500	-13.5400	-13.2700	-13.2300
Input for a weighted average	$\frac{-0.32}{-6.399}$ = 0.0500	$\frac{-0.1}{-6.399}$ = 0.0156	$\frac{-0.62}{-6.399}$ = 0.0970	$\frac{-0.08}{-6.399}$ =0.0130	$\frac{-0}{-6.399}$ =0

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor; *smaller-the-better; *i** - optimal parametric setting indicator; ***lowest rank; ****highest rank

Table 6. The normalisation of the parameters

Downtime causes (factors)	A	B	C	D	E	F	G	H	I	J
$\sum_{i=1}^{m} X_{ij}$	27	3	44	17	8	4	7	1	2	20

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

Table 7. Weightage according to WSM

Downtime causes (factors)	A	B	C	D	E	F	G	H	I	J
Weightage	0.0730	0	0.0031	0.6750	0.0734	0.0500	0.0156	0.0970	0.0130	0

Key: A - Replace pallet; B - Take a sample; C - Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

To introduce these weights into the WSM multicriteria structure, the decision matrix is first normalized by the formula in Equation (14):

$$DM_n = \frac{X_{ij}}{\sum_{i=1}^{m} X_{ij}} \quad (14)$$

Where DM_n is the formula for normalization, m relates to the number of parameters, X_{ij} is the value of the parameter and $\sum_{i=1}^{m} X_{ij}$ is the sum of the values for all the parameters.

This yields the values in Table 6. However, for the weighted sum method, Equation (15).

Weighted sum method, WSM = $A_i^{WSM} = \sum_{i=1}^{m} w_j X_i$ (15)

where w_j relates to the weightage and X_i relates to the normalized value for each cell. Furthermore, Table 7 shows the weightage according to WSM. Tables 8 and 9 show the computation of the WSM technique and the ranking table, respectively.

Table 8. WSM computation table

Downtime causes (factors)	A	B	C	D	E	F	G	H	I	J
Workstation 1	0.0431	0	0.0016	0	0.0092	0	0.0045	0.0970	0	0
Workstation 2	0.0297	0	0.0016	0.6750	0.0642	0.0500	0.0111	0	0.0130	0

Key: A - Replace pallet; B - Take a sample; C – Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

In the computation of the TWSM, TWPM and TWASPAS, the preference score is measured as the second to the final point, the ranking of the alternatives (workstations) is the final issue of concern in the evaluation process. The preference scores are essential indicators of how much importance each workstation is to the achievement of a minimum downtime for the packaging equipment in the animal feed production system. The workstation with good performance and hugely related to the minimization of the process downtime is assigned higher scores while the workstation assigned lower scores are those that perform poorly and are judged not substantially important to the reduction of the downtime of the packaging unit of the animal feed production process. In this article, the preference scores for the TWSM, TWPM and TWASPAS are indicated in Tables 9, 11 and 12, respectively with the summary of the preferences and ranks for each workstation displayed in Table 12, including the workstations score and ranking. It is here that the process engineer could establish if there is a significant difference between the candidate workstations.

Table 9. WSM ranking table

Downtime causes (factors)	WSM preference score	Ranking	Remark
Workstation 1	0.1553	2	Lowest ranking
Workstation 2	0.8446	1	Highest ranking

Furthermore, for the weighted product method, Equation (16).

Weighted product method, WPM = $A_i^{WPM} = \prod_{i=1}^{m} X_i^{w_j}$ (16)

where w_j relates to the weightage and $X_i^{w_j}$ relates to the normalized value for each cell. Besides, Tables 10 and 11 show the computation of the WPM technique and the ranking table, respectively.

Table 10. WPM computation table

Downtime causes (factors)	A	B	C	D	E	F	G	H	I	J
Workstation 1	0.9620	1	0.9980	0	0.8580	0	0.9810	1	0	1
Workstation 2	0.9360	1	0.9980	1	0.9900	1	0.9950	0	1	1

Key: A - Replace pallet; B - Take a sample; C – Stamp label; D - Input data; E - Sawing machine problems; F - Change feed; G - Take a sack; H - Take a thread; I - Problem with packing machine; J - Briefings with supervisor

Table 11. WPM ranking table

Downtime causes (factors)	WPM preference score	Ranking	Remark
Workstation 1	6.7990	2	Lowest ranking
Workstation 2	8.9090	1	Highest ranking

Besides, for the WASPAS method, Equation (17) is shown.

WASPAS = $Q_i = \lambda Q_i^1 + (1-\lambda)Q_i^2$ (17)

where λ =0.5, Q_i^1 and Q_i^2 are preference scores of WSM and WPM, respectively. Furthermore, Table 12 shows the computation of the WASPAS technique and the ranking table.

Table 12. WASPAS computation table

Description	Q_i^1	Q_i^2	$\lambda Q_i^1 + (1-\lambda)Q_i^2$	Ranking
Workstation 1	0.1553	6.7990	3.4800	2
Workstation 2	0.8446	8.9090	4.8770	1

Key: *Highest ranking, **Lowest ranking

Furthermore, in the report given by Rahmawan et al. (2020), four activities were identified as the biggest contributors to downtime in the production process studied. These are the stamp label activity, pallet change, data input and communication with the supervisor. However, since only Pareto analysis was used, the tool is not competent to optimize the factors but only arrange according to the provided weights. Thus, the suggestion by the Pareto method may be taken as sub-optimal. However, by applying the Taguchi method to the factors, the worst four factors were established using their delta values (Table 5) as input data (delta value of -4.32 and offered by the 9th position), take a thread (delta value calculated as -0.62 with the 8th position assigned to it), sewing machine problem (delta value of -4.47 and assigned to 7th position) and replace pallet (delta value of -0.469 and offered the 6th position). By comparing these results and those of Rahmawon et al. (2020), it is surprising to note that only two of the factors are common to both studies. These are replace pallet and input data. By comparing the results of these two sources, the optimized form input data leads as the worst factor instead of the stamp label activity suggested by Rahmawan et al. (2020). It means that efforts should be directed at enhancing the performance of the input data factor as it will substantially improve the overall performance of the input data factor as will substantially improve the overall performance of the animal feed plant. The result that promotes the input data as the worst factor was confirmed by the outcome of WSM, which offered the highest weight of 0.6750 to it. This means that the results given by the WSM are already optimized before its selection by the method.

However, by making judgments on the performance of workstations 1 and 2 using the Pareto chart, one tends to prefer workstations 1 to 2 by comparing the differences in the hierarchy of factors prioritized by the Pareto chart. For instance, the differences of 0, -, -1, -8, -5, -4 and -3 in preference of workstations 1 to 2 are accounted for by the Pareto chart. Nonetheless, the results are not optimized. But in the optimized form, workstation 2 is presented as being better than workstation 1 as it has an optimized feature within it. The workstation 2 revealed a preference score of 4.8770 and ranked 1st against workstation I which displayed a preference score of 3.4800 and ranked in the 2nd position.

Besides, in this article, the results of the Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS methods are shown in Tables 9, 11 and 12. In the three tables, workstation 2 has the highest rankings of 0.8446, 8.9090 and 4.8770 for the TWSM, TWPM and TWASPAS, respectively. Also, the lowest rankings of 0.1553, 6.7990 and 3.4800 were recorded for workstation 1 using the Taguchi-WSM, Taguchi-WPM and Taguchi-WASPAS methods, respectively. However, from literature reports, WASPAS has been associated with the best results compared to WSM and WPM. Hence, from the various results of prioritizing workstations 1 and 2, the results of the TWASPAS are recommended.

4. CONCLUSIONS

In this paper, it was mentioned that the literature has just opened up and used a limited downtime analysis approach to rank the activities. In an interesting article by

Rahmawan et al. (2020), the results of two workstations in an animal feed transformation system revealed the chief contributions to downtime at the activities involving stamp labelling, pallet change, the input of data, activities on communication occurring between the workers and the supervisors. It is unclear how the downtime analysis could be optimized and consequently ranked. This paper forms a practical instrument for downtime analysis, considering the ten criteria suggested by Rahmawan et al. (2020). The principal result of this work is the creation of a Taguchi method to analyse the production factors through the institution of factor level issue, orthogonal array selection, analyses on the signal-to-noise ratio through the choice of relevant criteria among the smaller-the better. The response table that summarizes the signal to noise ratio is then created and linked to the multicriteria models of the weighted sum model by using the outcome of the lowest values for each level in all factors as inputs, such as the weight for the factors.

Finally, the ranks are obtained and compared to the proposal by Rahmawan et al. (2020). The method has been applied to a plant in a developing country that is engaged in the transformation of animal feed for chickens to reveal how the outcome of the research could be used in real-world situations. A principal conclusion of this work is that the Taguchi analysis cum weighted sum method multicriteria method applied to downtime analysis in animal feed production is straightforward to apply in practice. Nonetheless, it utilizes all the relevant downtime analysis factors in a manner, which is easily adaptable to a particular industrial perspective.

This research is limited to WASPAS and its associated methods of WPM and WSM. However, future studies may extend to other selection methods such as the PROMETHEE, TOPSIS and AHP and observe if the findings are uniform across selection methods. With the significance of tracking and correcting imprecision and uncertainty in the evaluation of decision parameters, it would be interesting to introduce fuzzy logic to evaluate and correct these uncertainty issues. As such fuzzy Taguchi methods could be combined with the WSM, WPM and WASPAS methods for greater assessment insights. There are advantages to channel efforts to parameters of high sensitivity and it also exposes weak parameters with little influence on the system. Thus another investigation may be conducted using variations of the downtime factors by some quantities to provide a direction on the investment of efforts on the parameters of downtime in the production process.

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