Enhancement of Maintenance Downtime using Poisson Motivated-Taguchi Optimisation Method

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Abstract

In an original article, an addition was made to the well-known Taguchi's methodical design literature by proposing how Poisson distribution may be incorporated into the Taguchi method for enhanced performance analysis in optimisation. While the article is recent, it was found compelling enough to apply this novel concept of Poisson distribution to a growing area of maintenance research known as maintenance downtime analysis. Consequently, this paper contributes to the expanding research neighbourhood through a Taguchi optimisation method based on Poisson distribution related to the maintenance process optimisation. A valuable method to optimise maintenance downtime was developed wherein the Poisson distribution was used to achieve the probability of maintenance downtime. An important foundation of the method is the Taguchi scheme. These elements were transformed into the factor-level design of the Poisson enhanced Taguchi scheme while the framework was tested using data from a process industry for validation. Interesting, the Taguchi's signal-to-noise quotient led to an enhanced set of limiting factors for better reliability of the system as $G_1H_1I_1J_1K_3$. By interpretation, the following was found: downtime (204.61 mins), probability density function (0.00187), and cumulative density function (0.00776). The combination of these factors and levels will enhance maintenance downtime in the process industry as a result of their contributions. The outcome revealed the competence of the model to optimisation schemes.

Keywords: Poisson, Reliability, Maintenance, Taguchi Method, Downtime

1. Introduction

1.1 General

With an increasing volume of literature on the use of Taguchi methods in maintenance settings, different scholars have emphasized the significance of the approaches to optimise maintenance parameters [1–5]. The proper characterisation of the maintenance optimisation parameters in a characteristic Poisson structure could assist the maintenance manager to obtain the true systematic behaviour of the maintenance system captured in evaluation [6–10]. It will as well help towards the attainment of the goals of maintenance [11, 12]. Consequently, building up a model to optimise the maintenance system with a demonstrated example on the food processing plant from a developing country's context is important. The Poisson–motivated Taguchi optimisation procedure is therefore contributed to this research.

The Poisson-enhanced Taguchi scheme (PETS) is considered as a largely promising optimisation methodology and with the potential of radically transforming the optimisation terrain [13]. With its initiation from the composite development scheme, the PETS is determined to transform engineering research to a matured, interesting and computationally intensive area [13]. Unfortunately, this new method, developed by Ajibade et al. [13] awaits further verification and a wide scope of testing in composite development and other areas of human endeavour. In this paper, it was found compelling to test the documented reports on this newly advanced scheme of Taguchi's method. Based on the fact that manufacturing plants are increasingly being challenged to update their scientific knowledge of maintenance in practice and the global influence of maintenance to the survival of the organisation, the attention of this study is directed to maintenance. Specifically, the interest is on optimising maintenance downtime of a food processing industry that depends on farm produce in an agriculturally-oriented community.

In an extensively cited work on the subject of maintenance optimisation, Dekker [14] argued on the

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significance of maintenance and shows how the proportion of workers engaged in maintenance have expanded. It further revealed that the proportion of maintenance expenditure to the total operating costs has grown over time. Evidence from Dekker [14] suggests that maintenance optimisation is central in an attempt to improve maintenance practices and that models involving probability distributions have been recognised in optimising maintenance [15]. However, the downtime issue and how Poisson distribution may be incorporated into the classical Taguchi optimisation model has not yet been considered in the literature [16–18]. In the following paragraphs, the relevant literature on maintenance is reviewed and the gap in knowledge is shown clearly.

A primary motivation of this research was to prevail on the limitations encountered by maintenance managers in the management of production equipment and consequently permit them to enhance efficiency. Maintenance managers are to benefit their companies from a reduction in wasted time and resources [19–22]. This reduces the efforts needed by the company to sustain a profit and eliminate unwanted stress to maintenance staff. Failure to avoid this leads to the depletion of employee's satisfaction and the manufacturing system is threatened by unnecessary faults and other challenges [23–25]. The motivation for the research was particularly to aid in minimising machine breakdown likelihood as the frequency of occurrence is predetermined. Although downtime had been predicted in the time past, the maintenance research community has failed to incorporate the rich potential of Poisson distribution into optimisation models [26–28]. To date, there is no single documentation that has integrated Poisson distribution and the Taguchi method into a robust framework for optimising downtime in manufacturing systems. The numbers of stages implemented in this novel framework is as follows. First, the limiting factors and levels are established. Second, the orthogonal arrays are given. Third, the choice of the quality characteristic among the lower-the-better, nominal-the-best, and the higher-the-better is made. Next, the Poisson motivated function is activated and substituted into the Taguchi scheme while making the S/N platform as the entry point. Finally, the optimal parametric setting is obtained.

The use of Poisson distribution to infuse the Taguchi methodical scheme, as opposed to the classical Taguchi methodical framework, for maintenance downtime minimisation was strongly motivated by the outstanding attributes which the Poisson distribution has, namely:

- The downtime data collection may be treated in an experimental manner whose product could be distinctly categorised in terms of machine uptime (successes) or machine downtime (failures)
- The likelihood that mechanical equipment will have an uptime is comparative to the dimension of the territory
- The mean amount of mechanical equipment uptime, which takes place in a particular territory is established
- The likelihood that the mechanical equipment has an uptime in a very miniature territory nearly zero.

Furthermore, while it is understood that part replacement is extremely expensive compared to maintenance, repair and overhaul (MRO) activities and that the later has a complex set of interrelated activities, scholars have paid comparatively extremely minor attention to how to reduce the cost of MRO activities despite considering all the necessary combination of parameters. Certainly, maintenance downtime activities are not exceptions as multiple tasks need to be performed but the cost needs to be drastically reduced. In a representative example, a few years ago, Graf et al. [29] proposed the advantageous full factorial design to examine all the influences and interfaces in a maintenance repair and overhaul coordinated tasks for laser metal deposition. Nonetheless, paying attention to the design of experiments in a drive towards experimental cost reduction and effectiveness is necessary if a comprehensive picture of maintenance optimisation in the face of Poisson distribution inducement is to be obtained. Thus, in this work, the design of experiments is proposed as a necessary tool for the new model of Poisson integrated with Taguchi method to work.

As a result of the foregoing, an effort has been invested to develop a structure to account for the minimisation of downtime using the Taguchi method that has Poisson distribution infused into it. The proposed model will offer a substantial and effective manner of implementing maintenance decisions in the food industry, enhancing communication between the maintenance decision-makers and the maintenance workers. A brief highlight of the substantial and advantageous attainments that the proposed scheme will offer includes:

- The approach will help maintenance managers in the food industry to optimise their routine maintenance activities by reducing downtime arising from equipment failures.
- The approach will enhance the association between maintenance decision-makers and labour unions since maintenance activity goals could be achieved more easily and objectively through optimisation.
- Increase in the motivation of maintenance workers when they know that their outputs are optimised and no leakages in performance exist. This will make the maintenance employees believe that they are objectively assessed.
- Enhance efforts in quantifying maintenance performance and improve the overall maintenance performance since what gets measured gets enhanced

1.2 Literature Review

The key objective of downtime minimisation is to avoid downtime cost, which results in billions of dollars in revenue yearly. Moreover, as a result of the increasing competitiveness of manufacturing organisations in customer satisfaction, the scope for downtime monitoring and control has escalated [24, 25]. Furthermore, as organisations offer more incentives to create and achieve production targets it is becoming extremely important to further analyse downtime and pursue how it could be enhanced optimally. In the current manufacturing scenario of intense value creation drive and zero downtime goal setting, the choice of the downtime models is extremely important. The need to incorporate the probabilistic features of downtime activities in terms of Poison distribution motivated characteristics is necessary for more precise evaluations of downtime [6]. Without the means of robust optimisation tools for downtime analysis, it becomes extremely difficult to quantify the outage tasks. It is challenging to know the scope of tasks to be carried out with clearly defined boundaries. An easy establishment of maintenance operational hazard will be difficult. The coordination of the maintenance crew in monitoring downtime will be unattainable. Further, budget planning and execution will be difficult to attain in the manufacturing plant. Besides, appraising maintenance systems using the Taguchi method alone could certainly oversight the advantages of using the Poisson-motivated technique. Consequently, all these issues stimulated the current scholars to conduct a study that appraises the maintenance downtime system to optimise and determine the characteristics of the framework when the Poisson distribution is infused into the Taguchi methodical structure.

Repairable equipment in manufacturing systems will obviously suffer downtime due to numerous problems of component failure, inappropriately applied skills of employees to manage the machine when needed, starvation of the required resources for smooth running such as water, electricity and lubricants, unattended warnings of a forthcoming breakdown through elevated noise levels and even deliberate damage by poorly motivated staff from welfare deprivations. For production to continue, effective strategies should be implemented to correct the downtime problem, reduce or eliminate its future occurrence. Downtime is regarded as the largely substantial contribution to the inefficiency of systems. However, the new manufacturing enhancement movement wherein near-zero downtime is targeted by the manager on the production floor cautions carefree attitudes of workers while promoting scientific quantifications in modelling and analysing downtime. As a response to this movement, the literature is reviewed and the necessary gaps are subsequently identified. Furthermore, observation from an insight into the literature is given. So the literature is reviewed as follows:

In the downtime area, very few mathematical modelling articles were found tackling the steps to appraising the downtime of a system. Papers investigating downtime with the use of mathematical models include Hussin and Hashin [30], Jung et al. [31] and Nwanya et al. [32]. In their study on downtime costs in manufacturing systems, Liu et al. [27] introduced the idea of the concurrence of downtime at various phases and analytically determined through a practical calculation how serial multistage units within the manufacturing systems could be affected. They reveal that with real-time data from the production floor an easy derivation and implementation of the evaluation procedure could be made. They also claimed that the procedure aided decision making at the factory and could be easily applied to aid the establishment, ordering and distribution of budgets in a multi-phase system of manufacturing. From the study by Al–Bashir et al. [33], it was established that six sigma ideas and instruments could be applied to design and perform corrective maintenance actions and processes employed to preserve and restore medical equipment in the public health division of Jordan. The results obtained in their research revealed that the principal parameters impacting on downtime include the time to check, decide and deliver but excludes the real maintenance time. Furthermore, staff availability was not the principal parameter influencing the downtime is negatively impacted by the setback to detect breakdown, failure of devices, the setback in the registration call for service, the setback in work order close–up and corrective maintenance not functioning as intended.

My–Abdelbar et al. [34] conducted a study on downtime analysis to enhance the performance of equipment using reliability, safety, availability and maintainability as the target measures. Their investigation also comprised of a wide range of methods, including cause–and–effect diagrams, root–cause–analysis approach, FMECA, 5W, and ABC analysis. They insinuated from their research that the approach offered a superior solution by means of enhanced life of the equipment. Nwanya et al. [32] made an effort to investigate the production downtime for a Nigerian plastic plant. To offer a robust framework, a procedure for uptime maximization was suggested. Their findings include a noteworthy growth of production rate in the diverse product consideration between 90 and 240 units, Knezevic [26] attempted to search for the solution to improper planning in maintenance by offering a novel method for a quick, precise prediction of downtime in a cluster replacement maintenance strategy. In their research, they focused on three different criteria that specify which replacement activities are carried out: concurrently, consecutively and jointly. Form their investigation they included that the model offered is useful and application in diverse maintenance systems. Salonen and Tebikh [28] investigated the opinions and mindsets concerning downtime costs in manufacturing industries in Sweden. From their study, they concluded that the respondents exhibit unclear thoughts concerning the cost related to downtime. They further stated that they infrequently measure the downtime costs, which are related to the maintenance of equipment. Al–Chalabi et al. [35] through their study conducted a reliability analysis to reveal the true state of downtime concerning four drilling machines. Using the Swedish underground mining activities as a case study, their model attributed the elevated downtime to feeders and hoses.

Smith and Dekker [36] obtained an estimation procedure to calculate the anticipated downtime and the anticipated costs per unit for the process while prior knowledge of the complete amount of units well as the value of age–replacement is declared. The paper was reviewed here so as to gain insight into the redundancy schemes in maintenance such that foaled equipment is immediately interchanged with active ones while the effectiveness of corrective maintenance in repairs is determined for the broken–down units. In order to explore the downtime limiting potential in manufacturing equipment, Zou et al. [37] analysed the influence of downtime on the systems inefficiency using criteria such as stoppage period of a machine, dynamics of the systems butter threshold, alteration in systems future characteristics as well as the systems production level at a future period. A set of cases were reported as tools to establish the effectiveness and accuracy of the proposed models. Grace and Christiansen [38] explored the drawbacks of downtime and reviewed the literature concerning downtime activities involving 388 joint-cycle plants of the classes 164D/E and 224F for gas turbines. It grouped the study on the basis of the 15-year period with more than 3000 unit years of data points. The authors reported the causal factors for downtime and their recorded durations. It further documented unscheduled maintenance, availability and reliability and cost estimates for lost revenues. The risk – rooted appraisal method is portrayed by the author states an array of likely costs for downtime activities that are not planned for.

1.3 Problem identification

The existing literature on downtime clearly uncovers the fact that a growing number of research articles have proposed several interesting and insightful method downtime modelling and analysis. Nonetheless, insufficient literature exists on the development of optimal results for downtime. Fewer models have tackled downtime optimisation in process plants. However, no study has examined downtime in the developing country context such as Nigeria with a different social, political and economic framework compared with the developing nations. No study has been recorded for the process industry globally with the aim of optimising downtime using the integrated tools of the Taguchi methodical scheme and Poisson distribution. By putting in mind the above issues, the subsequent literature gaps have been established and ought to be tackled:

- The use of Poisson-motivated Taguchi method to optimise downtime in process industries ought to be tackled with the unique related parameters of statistical functions, reliability measures, and hazard functions
- Employment of Taguchi method with the outstanding and classical features of an orthogonal array, levels and factor definition from the existing industrial data needs to be implemented from this perception, a clear understanding of the focus for the study emerges as objectives, following:
- To disclose the tactic entailed to appraise and calculate the optimal parametric values of downtime using the Poisson-enhanced Taguchi method and assist the maintenance engineer to reduce downtime for maximum benefit derivation
- To explore the substantial and appropriate parameters that interfere with downtime in the optimisation with downtime

2. Methodology

2.1 Maintenance data

In this article, the unique goal of optimising the downtime and its related parameters was pursued through the Taguchi method. A novel framework proposed by Ajibade et al. [13] was verified in a maintenance setting. In this innovative model, Poisson distribution was infused into the Taguchi methodical framework and the case study data was collected from the maintenance section of an active manufacturing plant operating in the southwestern part of Nigeria. The data was collected from the records in the plant, which details out historical information on repairs of machines and ascertains the level of achievement of all daily repair and maintenance targets. Interesting data includes those concerning faults on various equipments, duration of faults before being cleared and the production line where such faults occur. The scheme of the research is shown in Figure 1.

The maintenance manager was consulted for the records of maintenance data of a food processing company for January to August 2017, which is a total of 35 weeks. The data consists of the downtime, number of equipment failures by category of lines, mean time to repair (MTTR) and mean time between failures (MTBF). The downtime was later used to calculate for the probability density function, cumulative density function, reliability and hazard rate for each of the 35 weeks using the relevant equations. On a daily basis and as per production lines these data are gathered and the period of downtime is also noted. Maintenance data was collected from a process industry and the total downtime for the system per week for thirty-five weeks was obtained. The downtime was then analyzed using Weibull distribution with a scale parameter of 324.57 and a shape parameter (ß), which was used to obtain the probability density function (PDF), cumulative density function (CDF), reliability and hazard rate of the system per week for the thirty-five weeks.

Probability density function

The PDF has been chosen as an impact parameter for the Taguchi process in the evaluation of the optional parametric setting for the maintenance process using the Poisson–stimulated function embedded in the Taguchi method. PDF has its root in probability theory. It explains the comparative chances of a maintenance event that is treated as a random variable to be assigned a specific value which best describes the activities of the maintenance crew in the system. The likelihood of this maintenance activity variable falling in an array of values is explained by an integral for the maintenance activity's variable density when the range is considered. The literature describes this as the area covered by the density function which is on top of the parallel alignment as well as flanked by the smallest and the highest values in the span.

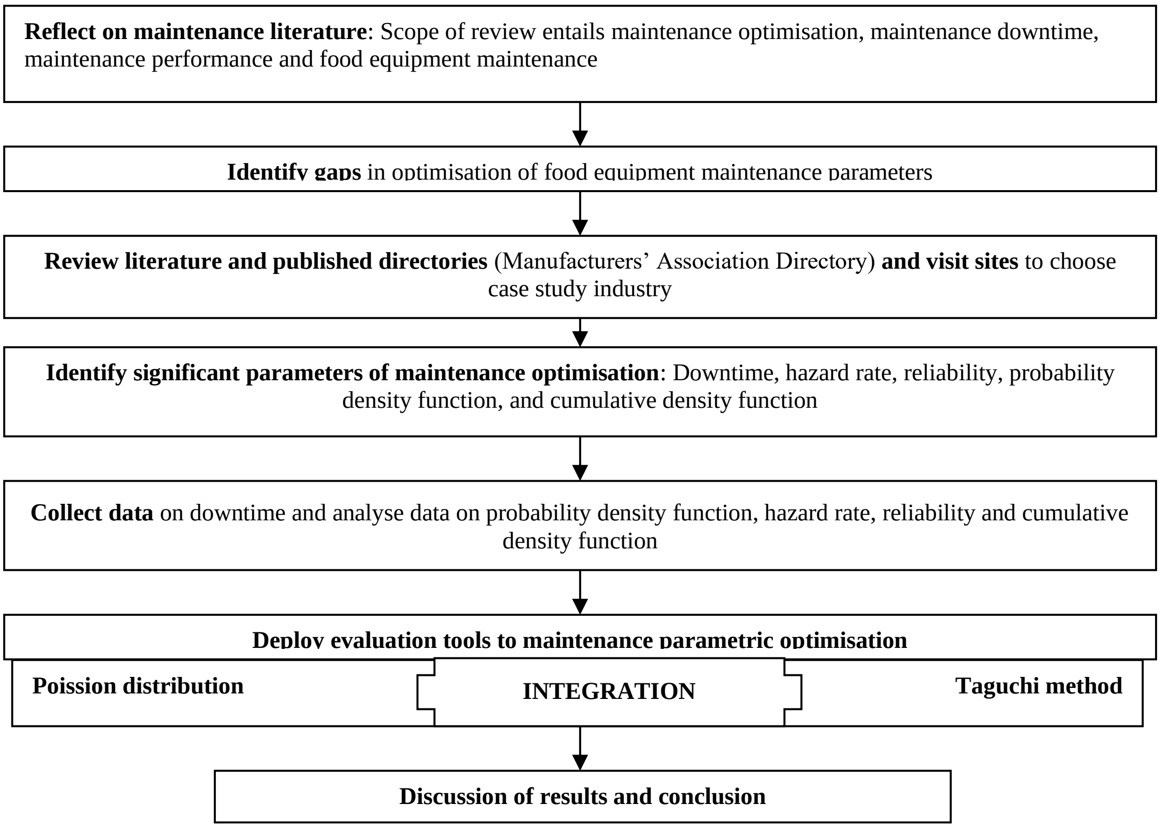

Figure 1: Scheme of the study

The Weibull PDF is given as [39, 40, 41]:

$$f(t) = \frac{\beta}{\eta^{\beta}} t^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} \quad \text{for } t \geq 0, \quad \eta > 0, \beta > 0 \qquad \ldots\ldots(1)$$

The symbols β and η are the scale parameter and the shape parameters of the distribution, correspondingly. The symbol t connotes time while $f(t)$ indicates the failure density function. The PDF was obtained using Equation (1). In the case study, the shape parameter was taken to be 3. This judgement was made based on how long the equipment has been in use, which is over 10 years. This period corresponds to the wear out stage according to the bathub theory. The scale parameter, eta (η) used was 324.57 hr. it was obtained by calculating for the 63.2 percentile downtime using Equation (2) [42]:

The 63.2 percentile,

$$P_{63.2} = (M/100)(N+1) \qquad \ldots\ldots(2)$$

where M is the percentile and N is the number of weeks, which is 35 weeks in the current study. The $P_{63.2}$ then gives 63.2/100 (35+1) = 22.75 week. It means that the scale parameter falls in the 22.75th week, which has 324.57 hr as its downtime.

Cumulative density function

This is another parameter used for the maintenance process. It explains the likelihood to have the maintenance manager with a throughput lower or at least the same as a particular value. Mathematically, if the throughput is presumed to take on a value of "t", then the cumulative density function, CDF=$F(t)$, that is a functional equivalent to the proportion of the maintenance crew exhibiting a throughput lower or at least the same as "t". Afterward, the cumulative density function representing the normalized throughputs regarding the mean maintenance crew member throughput concerning all the crew members is the process is established.

The Weibull CDF is given as Equation (3) [39–41]:

$$F(t) = \int_0^t \frac{\beta}{\eta^{\beta}} t^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^{\beta}} dx = 1 - e^{-\left(\frac{t}{\eta}\right)^{\beta}} \qquad \ldots(3)$$

Also, the symbols β and η are the scale parameter and the shape parameters of the distribution, correspondingly. The symbol t connotes time while $f(t)$ indicates the failure density function.

Reliability

The concept of reliability describes the likelihood that mechanical equipment in the process plant considered for investigation will achieve the anticipated function. It will not fail while the conditions of the mechanical equipment are measures under certain declared environmental and system parameters [41]. Although the growth in research has extended reliability to cover human aspects, this work limits its application to the mechanical equipment while the human aspect is not accounted for, but may be an interesting future research aspect [5, 43]. Thus, the process being investigated may be declared as having elevated mechanical equipment reliability if the system yields associated outcomes when subjected to a similar situation.

The Weibull Reliability (R(t)) is given as Equation (4) [40, 41]:

$$R(t) = 1 - F(t) \qquad \ldots\ldots (4)$$

Hazard rate function

The function offers an option to distinguish the spread of the random variates in the situation of maintenance downtime data analysis. The effective optimisation of maintenance parameters in a food processing industry should leverage on the hazard rate as a parameter of the maintenance processes. Hazard rate is an important element of survival statistics to predict the time elapse before failure of the major production equipment covered in this case study. In the food production lines, failures of major equipment for packaging, product filling, product discharging and other activities may result in substantial downtime and the analysis of failure (hazard) rate would be helpful to control the downtime. The paddle feeder failure is an example of a significant fault in the system that needs attention from time to time [44]. The hazard rate for the equipment in the food industry could be established employing the subsequent Equation (5):

$$h(t) = F(t) \;/\; R(t) \qquad \ldots\ldots(5)$$

where $F(t)$ indicates the probability that the quantified value of equipment failure will occur within a defined time interval, for instance, a particular week. This is also referred to as the probability density function. The $R(t)$ connotes the survival function otherwise referred to as the probability that all the equipment, considered as a group, will not fail over a particular time (t).

Hazard rate was promoted by earlier researchers in maintenance, including Dhillon [45] as a value that cannot attain a negative threshold and one that assumes a bathtub resemblance in shape. As applied to the food equipment under study, the behaviour of the equipment with respect to failure rate is a downward sloping curve at the beginning. This shows a decaying failure (hazard) rate. The second segment of the bathtub remains constant and then the hazard rate starts to shift towards an upward direction. Thus, the bathtub behaviour could be further explained this manner: When the food production equipment was newly installed, the various equipment are least expected to fail in the early years of usage. Nonetheless, a growth in the probability of failure of any equipment within the food production lines becomes evident. As the bathtub curve slopes upward, the substantial and productive life (useful life) of the food equipments expires and there is likelihood that non-random occurrence of faults occurs in the food equipment.

2.2 Taguchi optimisation

After analyzing the maintenance downtime with Weibull distribution, the values of the probability density function (PDF), cumulative density function (CDF), reliability and hazard rate obtained are of dissimilar range. The thirty-five values of each of the factors (probability density function, cumulative density function, reliability and hazard rate) are grouped into four which is used levels, each group consisting of nine values, except the fourth group which has eight values. The mean value of probability density function (PDF), cumulative density function (CDF), reliability and hazard rate in each group were obtained and are used as factor levels for Taguchi optimisation as shown in Table 1

Table 1: Limiting factors and levels

S/No	Limiting Factors	Levels			
		1	2	3	4
1	G: Downtime (hr)	204.61	215.70	335.8489	460.1938
2	H: PDF	0.00187	0.00232	0.00278	0.00166
3	I: CDF	0.24446	0.22442	0.55512	0.83555
4	J: Reliability	0.75554	0.77558	0.44488	0.16445
5	K: Hazard Rate	0.00352	0.00330	0.00776	0.01435

The formulation (4 factors and 4 level optimisation) described in Table 2 were solved using an appropriate orthogonal array which was generated using Minitab 18 statistical software. The $L_{16}4^5$ orthogonal array used is shown in Table 2.

Table 2: The $L_{16}4^5$ orthogonal array

S/No	G	H	I	J	K	S/No	G	H	I	J	K
1	1	1	1	1	1	9	3	1	3	4	2
2	1	2	2	2	2	10	3	2	4	3	1
3	1	3	3	3	3	11	3	3	1	2	4
4	1	4	4	4	4	12	3	4	2	1	3
5	2	1	2	3	4	13	4	1	4	2	3
6	2	2	1	4	3	14	4	2	3	1	4
7	2	3	4	1	2	15	4	3	2	4	1
8	2	4	3	2	1	16	4	4	1	3	2

Key: G: Downtime(hr), H: PDF, I: CDF, J: Reliability and K: Hazard Rate

The smaller-the-best is the best quality defining the feature in this research to obtain higher reliability of the system because the lower the downtime, the higher the reliability of the system. The objective function is defined according to the smaller-the-best standard defining feature in Equation (6) [46]:

$$S/N = -10 * \log10(1/n * \sum y_i^2) \quad (6)$$

where S/N = signal-to-noise ratio, n = number of levels and y = the value of each level

Signal–to–noise quotient, abbreviated as the S/N or SNR, is popular evaluation index that weighs the signal (useful outcomes of the maintenance system) against noise (unwanted distractions and non-value adding activities of the maintenance system). The S/N values have a strong forward impact on the likelihood that an error will appear in the maintenance process. The nature of the noise is such that it goes beyond what the maintenance manager could direct. However, in many systems such as the maintenance process the maintenance manager has the advantage of expanding the intensity of the signal while holding the noise aspect constant to obtain higher quotient values for the SNR. This effort leads to a reduction in the likelihood of an error occurring. In the application of SNR for the Taguchi's method, often negative values are obtained. The negative values show that the noise power far exceeds the signal power, represented in mathematical expressions as Signal (Power) – Noise (Power) <0, where the unit of measurement is decibels (dB).

2.3 Poisson-motivated Taguchi Optimisation

The Poisson distribution can be referred to as distinct probability distribution of the number of events occurring in a particular place, time or period, given the mean number of times the event occurs over that time period. The values of each factor (downtime, probability density function (PDF), cumulative density function (CDF), reliability and hazard rate) for each level were recorded as observations. The mean of the values in all levels of a particular factor is taken as the mean of observation per interval. The Poisson distribution can be applied to the optimisation problem in Table 1 using Equation (7)

$$P\,(k \text{ event}) = (\varsigma^{-\lambda}\lambda^{k})/k! \quad (7)$$

where λ = mean number of observations per interval, ς = Euler's number, 2.718 and k = Observation number, 0, 1, 2,…

The Equation (7) was employed to obtain another collection of values from the event as shown in Table 3. These collections of values were used to multiply the matching value of an event in the Taguchi optimisation problem in Table 1 to produce the Poisson motivated observations as shown in Table 4

Table 3. Poisson Distribution

S/N	Limiting factors	Levels			
		1	2	3	4
1	G: Downtime (hr)	2.707E-130	4.116E-128	4.172E-126	3.172E-124
2	H: PDF	0.00220	0.00000241	0.00000000177	0.0000000000009739
3	I: CDF	0.29200	0.06800	0.01100	0.00120
4	J: Reliability	0.31300	0.08400	0.01500	0.00200
5	K: Hazard Rate	0.00710	0.00003	0.0000001235	0.000000000667

Table 4: Poisson motivated observation

S/N	Limiting Factors	Levels			
		1	2	3	4
1	G: Down time(hr)	5.5388E-128	8.8783E-126	1.4012E-123	1.4597E-121
2	H: PDF	4.11097E-06	5.60165E-09	4.92647E-12	1.61475E-15
3	I: CDF	0.071381838	0.015260512	0.006106342	0.001002663
4	J: Reliability	0.236484537	0.065148779	0.00667317	0.000328895
5	K: Hazard Rate	2.49866E-05	8.49914E-08	9.58255E-10	9.57407E-12

3. Results and discussion

On the account of the insight gained into the literature review carried out in a previous section of this paper, the development of an instrument to capture the Poisson characteristics of the maintenance system and data in the event of optimisation of process parameters was conceived as a research theme for this work. This requires the collection of industrial data to gain insight into the current state of the food processing industry that may be further analysed to carve out a methodology for the maintenance policy decisions. As such, this section of the paper deals with the results of the obtained data from the industry. The thirty-five data sets, which comprise of the weekly data for downtime, probability density function, cumulative density function, reliability and hazard rate were grouped into four levels, where the first level is the average of the value of the first nine weeks for each of the aforementioned parameters. The values for the second level are the averages for the parameters in the tenth to the eighteenth week. Likewise, for the third level, the averages for the parametric values for the nineteenth to the twenty-seventh weeks are obtained. Finally, only eight datasets were averaged for the fourth level because it has the remaining data. The ANOVA table is obtained (Table 5) by using the ANOVA feature in Microsoft Excel software to know the level of contribution of each factor. From this table, it can be noted that the contribution of downtime in variance analysis is the highest, followed by CDF and reliability while PDF and hazard rate are the least contributors to the variance analysis. None of the contributing factors can be neglected because their values are not too negligible.

3.1 Taguchi method

The limiting factors are downtime, probability density function, cumulative density function, reliability and hazard rate with their levels which are taken into account are shown in Table1. Experimental trials were carried out using Taguchi's $L_{16}4^5$ orthogonal array as shown in Table 2 (with 5 factors and 4 levels) which allows you to consider a selected subset of combinations of multiple factors at multiple levels for the optimisation of maintenance time as shown in Table 6.

Table 5a. ANOVA Table showing sum, average and variance for maintenance parameters

Limiting Factor	Count	Sum	Average	Variance
G: Down time(hr)	4	1216.355972	304.0889931	14361.82701
H: PDF	4	0.008634303	0.002158576	2.50799E-07
I: CDF	4	1.859551977	0.464887994	0.083982891
J: Reliability	4	2.140448023	0.535112006	0.083982891
K: Hazard Rate	4	0.028935518	0.00723388	2.67399E-05

Table 5b. ANOVA Table showing the F and *p*-values for maintenance parameters

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Rows	8617.817	3	2872.606	1.00009	0.426184	3.490295
Columns	295414.5	4	73853.61	25.71194	8.29E-06	3.259167
Error	34468.17	12	2872.347			
Total	338500.4	19				

Table 6: Taguchi $L_{16}4^5$ Experimental design maintenance modelling in a process industry

S/N	G: Downtime(hr)	H: PDF	I: CDF	J: Reliability	K: Hazard Rate	S/N
1	204.61	0.00187	0.24446	0.75554	0.00352	-40.198003
2	204.61	0.00232	0.22442	0.77558	0.00330	-40.198005
3	204.61	0.00278	0.55512	0.44488	0.00776	-40.197990
4	204.61	0.00166	0.83555	0.16445	0.01435	-40.198012
5	215.70	0.00187	0.22442	0.44488	0.01435	-40.656560
6	215.70	0.00232	0.24446	0.16445	0.00776	-40.656545
7	215.70	0.00278	0.83555	0.75554	0.00330	-40.656656
8	215.70	0.00166	0.55512	0.77558	0.00352	-40.656622
9	335.85	0.00187	0.55512	0.16445	0.00330	-44.502291
10	335.85	0.00232	0.83555	0.44488	0.00352	-44.502313
11	335.85	0.00278	0.24446	0.77558	0.01435	-44.502304
12	335.85	0.00166	0.22442	0.75554	0.00776	-44.502302
13	460.19	0.00187	0.83555	0.77558	0.00776	-47.238241
14	460.19	0.00232	0.55512	0.75554	0.01435	-47.238232
15	460.19	0.00278	0.22442	0.16445	0.00352	-47.238216
16	460.19	0.00166	0.24446	0.44488	0.00330	-47.238220

The values of Signal-to-Noise (S/N) ratio in Table 5 is used to obtain the Taguchi S/N ratios response table as shown in Table 7

Table 7: Taguchi S/N ratios response table for maintenance modelling in a process industry

Level	Downtime(hr)	PDF	CDF	Reliability	Hazard Rate
1	**-40.198002**	**-43.148774**	**-43.148768**	-43.148798	-43.148783
2	-40.656596	-43.148774	-43.148771	-43.148793	-43.148793
3	-44.502303	-43.148791	-43.148784	-43.148771	**-43.148770**
4	-47.238227	-43.148789	-43.148806	**-43.148766**	-43.148777
Delta	7.04022	0.00002	0.00004	0.00003	0.00002
Rank	1	5	2	3	4

According to Zareh et al. [47], irrespective of the quality characteristic used, a higher S/N ratio indicates the desired quality characteristic is being met. From the Taguchi S/N response values in Table 6, the enhanced setting of limiting factors for better reliability of the system is $\mathbf{G_1H_1I_1J_4K_3}$ which can be read from Table 1 as Downtime of 204.61 hr, PDF of 0.00187, CDF of 0.24446, Reliability of 0.16445 and Hazard Rate of 0.00776. . Combination of these factors and levels will enhance maintenance downtime in the process industry as a result of their contributions. The desired /suitable settings for the maintenance downtime optimisation is analyzed graphically in Figures 2-6 for Downtime of 204.61 hr, probability density function, cumulative density function, reliability and hazard rate.

From Figures 2 to 6, the scale in Y-axis is not the same but have a much closed values because of the values obtained for the PDF, CDF, Reliability, Hazard rate which later makes the result of the signal to noise ratio to the too-close after calculating for the each week and the difference between the values for each week is very small. Therefore, the difference in values of the SN ratio is very small almost with a value of greater than 0.00001.

3.2 Poisson motivated-Taguchi Analysis

Experimental trials were carried out on the Poisson motivated observation (factors level) in Table 4 using Taguchi's $L_{16}4^5$ orthogonal array as shown in Table 8 (with 5 factors and 4 levels) which allows you to consider a selected subset of combinations of multiple factors at multiple levels for the optimisation of maintenance time as shown in Table 9.

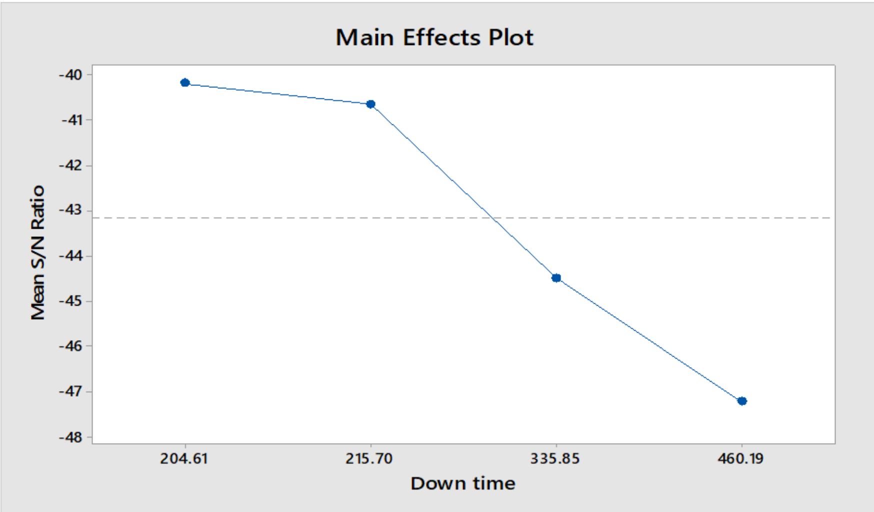

Figure 2: Main effect plot for downtime

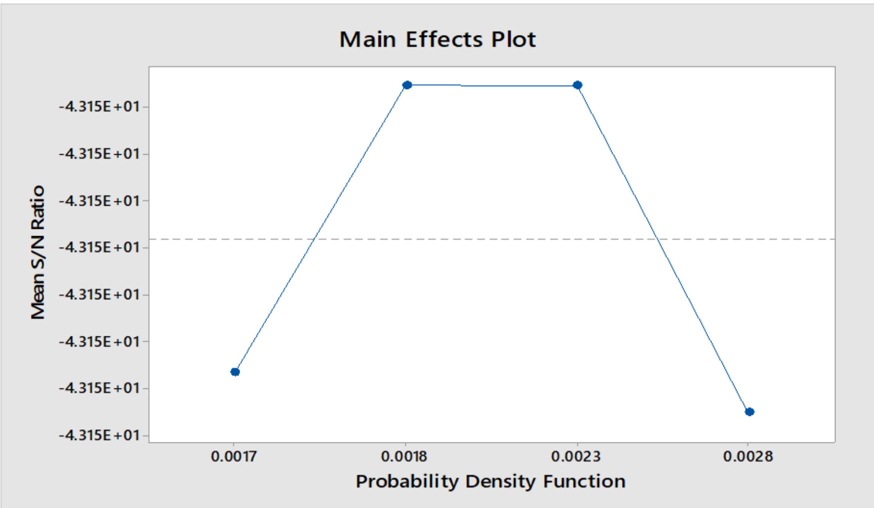

Figure 3: Main effect plot for the probability density function

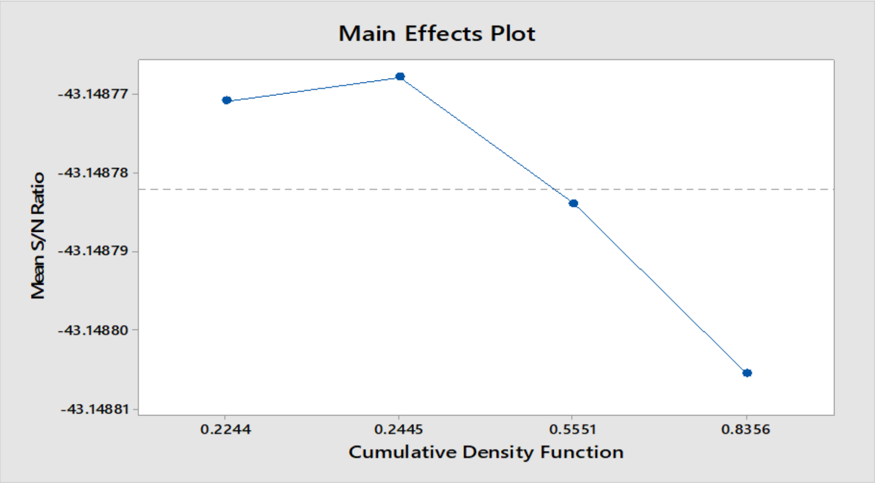

Figure 4: Main effect plot for the cumulative density function

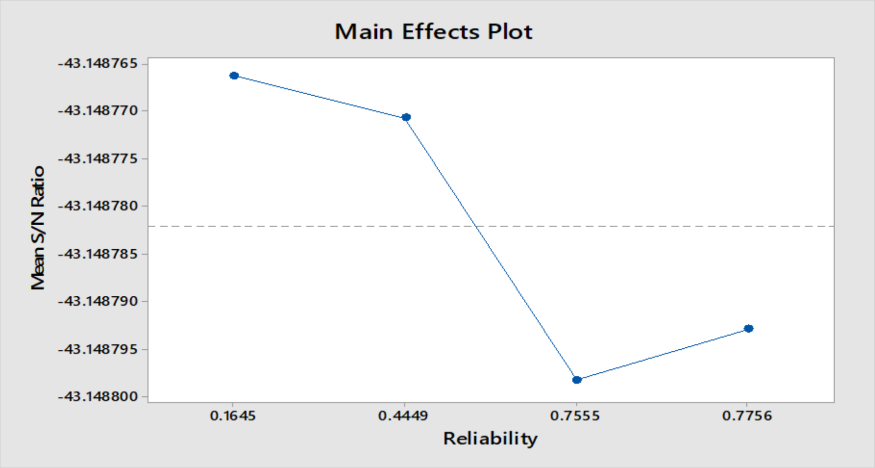

Figure 5: Main effect plot for the cumulative density function

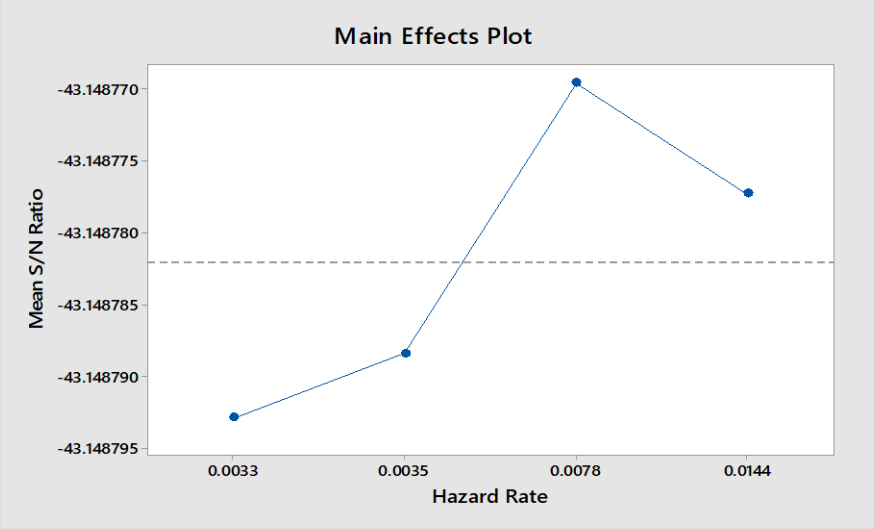

Figure 6: Main effect plot for the cumulative density function

Table 8: Taguchi $L_{16}4^5$ Experimental design maintenance modelling in a process industry

S/No	G: Downtime(hr)	H: PDF	I: CDF	J: Reliability	K: Hazard Rate	S/N
1	5E-128	0.0000041	0.07130	0.23640	0.000029	18.16953
2	5E-128	5.6E-09	0.01520	0.06510	0.000000085	29.51845
3	5E-128	4.9E-12	0.00610	0.00660	9.6E-10	46.94810
4	5E-128	1.6E-15	0.00100	0.00032	9.6E-12	65.59721
5	8E-126	0.0000041	0.01520	0.00660	9.6E-12	41.63359
6	8E-126	5.6E-09	0.07130	0.00032	9.6E-10	28.95872
7	8E-126	4.9E-12	0.00100	0.23640	0.000000085	18.54757
8	8E-126	1.6E-15	0.00610	0.06510	0.000029	29.71101

9	1E-123	0.0000041	0.00610	0.00032	0.000000085	50.30207
10	1E-123	5.6E-09	0.00100	0.00660	0.000029	49.53107
11	1E-123	4.9E-12	0.07130	0.06510	9.6E-12	26.32565
12	1E-123	1.6E-15	0.01520	0.23640	9.6E-10	18.52973
12	1E-121	0.0000041	0.00100	0.06510	9.6E-10	29.74796
14	1E-121	5.6E-09	0.00610	0.23640	9.6E-12	18.54476
15	1E-121	4.9E-12	0.01520	0.00032	0.000029	42.38179
16	1E-121	1.6E-15	0.07130	0.00660	0.000000085	28.92175

Table 9 reveals the Taguchi's orthogonal experimental design for the maintenance system considered with reliability and hazard rate indicated as the responses. The patterns of these responses are discussed below:

- *Reliability*: The reliability was 0.23640 in the first experiment and described by 72.46% of the original value in the second experiment. There was a constant decline in the reliability of equipment in successive experiments until experiment six. Again in experiment seven, substantial enhancement was documented probably due to renewed policies of timely delivery of spares by contractors and the timely assignment of maintenance workers to failed production equipment. Instability was found in the decline rate as the values of reliability occasionally rose to 0.23640 in experiments twelve and fourteen before finally declining by 97.21% in its final state in experiment sixteen
- *Hazard rate function*: The value of the hazard rate decline drastically from an initial value of 0.000029 in the first experiment to 9.6×10^{-10} in the sixth experiment indicating a very healthy circumstance in the process industry where the probability of being injured has significantly dropped. This unfortunate rose in the seventh experiment substantially and fluctuated in the high hazard rate region until experiment ten where it now drastically dropped again in favour of safety for the process plant in the fourteen experiments before being worsened again until the final value of 8.5×10^{-8} in the sixteenth experiment

Table 9: Poisson motivated-Taguchi S/N ratios response table for maintenance modelling in a process industry

Level	G: Downtime (hr)	H: PDF	I: CDF	J: Reliability	K: Hazard Rate
1	40.05832	34.96329	**25.59391**	**18.44790**	34.94835
2	**29.71273**	**31.63825**	33.01589	28.82577	31.82246
3	36.17213	33.55078	36.37648	41.75863	**31.04613**
4	29.89906	35.68993	40.85595	46.80995	38.02530
delta	10.15926	4.05168	15.26204	28.36205	6.97918
Rank	1	5	3	2	4

From the S/N ratio response Table 9, the enhanced setting of limiting factors for better reliability of the system is $\mathbf{G_2H_2I_1J_1K_3}$ which can be read from Table 1 as downtime of 215.70 hr, PDF of 0.00232, CDF of 0.24446, reliability of 0.75554 and hazard rate of 0.00776. As a result of their contributions, a combination of these factors and levels will enhance maintenance downtime in the process industry. In this investigation, the case of a food processing plant located in the southern part of Nigeria is reflected. Experimental trials were conducted with the Poisson – stimulated concept for the Taguchi methodical scheme. Through the application of the orthogonal array to maintenance modelling with consideration for downtime, PDF, CDF, reliability and hazard rate, the signal–to–noise ratio was obtained and the Poisson–stimulated Taguchi S/N ratio response table developed to display the characteristics of the process plant being investigated. Finally, the enhanced setting of the limit factors for superior reliability of the system was obtained. The outcome of the enhanced setting for the limiting factors for superior reliability suggests that the plant should operate with downtime (215.70 hr), probability density function (0.00232), cumulative density function (0.24446), reliability (0.75554) and hazard rate (0.00776). This implies that more training should be organized to workers to further appreciate the significance of enhanced downtime reduction through intensive preventive maintenance activities and the management should also pursue the timely usage of original spares to guarantee less breakdown and elevated reliability

4. Conclusions

In this article, a novel framework called the Poisson-motivated Taguchi scheme was developed and applied to a food engineering industry. The article analysed the maintenance downtime using the Poisson distribution and obtained the cumulative density function, probability density function, reliability and hazard rate as important parameters to reflect the state of affairs in maintenance activities. Data was collected over thirty-five weeks to verify the framework. The parametric settings for optimum performance can be achieved at downtime (level two), PDF (level two), CDF (level one), reliability (level one) and hazard rate (level three). The combination of the parametric setting will enhance a better performance of the equipment. While the first launch of this framework was reported on tensile property optimisation by Ajibade et al. [13], this is the first research article to document the application in maintenance settings. In further research, the approach could be applied to evaluate downtime but with the R-chart and X-bar chart substituted for the level determination to monitor and control downtime almost instantly as they occur in the production process. Also, the concepts of Taguchi–Pareto and Taguchi–ABC could be adopted as good candidates to solving the prioritisation problem while attempting to tackle the downtime issue in maintenance. Furthermore, a combination of Taguchi method and fuzzy logic as guided by Ighravwe and Oke [48] may be a fruitful future research method.

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