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Design of Experiments for Vibration Monitoring of Rotating Machinery

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Abstract

The valuable resources are rotating technology. In industrial applications, several machines are essential to the effective operation of any system. This article describes the engineering process for developing designs for analyzing variation and the optimization of condition monitoring by the impacts of vibration parameters using Taguchi processes to improve the quality of manufactured items. Crucial spinning equipment is included in the experiment to maximize the vibration frequency reactivity. Using Minitab 16 software, a Taguchi orthogonal array with three vibration parameter levels is built. The Taguchi approach minimizes quality characteristic changes caused by uncontrolled parameters by emphasizing the significance of examining response variation using the signal-to-noise (S/N) ratio. "The larger-the-better" was the principle that guided when it came to vibration frequency as a qualitative attribute. In order to investigate the performance characteristics, the impact of process factors on the condition monitoring process is examined using an examination of variance (ANOVA). Because it minimizes the number of tests and identifies the important parameter, it is also anticipated that the Taguchi technique will be an effective means to optimize different vibration parameters.

Keywords: Taguchi method, orthogonal array, vibration parameters, rotating machinery, ANOVA, Signal to noise ratio

INTRODUCTION

Unbalanced machine factors, misaligned aerodynamic forces, etc. are every result of vibration.

Vibration magnitudes of the horizontal direction are larger than those of the axial and vertical directions. The vibration analysis demonstrates that the accelerometers and sensors mounted on bearing locations of the rotating machinery can monitor the status of the rotating machinery, such as unbalance, misalignment, fatigue wear, and bearing condition. If these defects are not diagnosed the catastrophic failure of the machinery is imminent and hence the diagnosis must be carried out from the operational safety point of view. Fault detection is now more vital than ever since manufacturing equipment must perform better, be safer, and be more durable.

Conventional testing techniques are quite intricate and challenging to execute.

The number of experiments required increases with the number of process parameters. Taguchi's experimental design method has emerged as a powerful tool. Design of experiments (DoE) is a method of discovering and investigating every scenario that could come up in a multi-factor experiment.

DoE provides a method for investigating the simultaneous effects of multiple input variables, called factors on an output variable known as response.

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Vibration monitoring consists of a series of tests, in which changes are made to factors and the response is collected. An attempt is made to establish a procedure to identify the process conditions that influence vibration and then determine the set of input variables (or design factors) (frequency, *f,* Hz; locations of measurement, *l,* and direction of measurement, *d*), that maximize vibration behavior, *v* (or response).

LITERATURE REVIEW

Production industries require a variety of diagnostic technologies for monitoring vibration, lubrication, structural conditions, and electrical characteristics. Industry-specific combinations of parameters were used to run the system efficiently to maximize profit and minimize the total cost of production [1]. To failure detection in rotating equipment, a range of sensors might be employed to gather readings, including stator voltages and currents, air gap and external flux densities, rotor position and speed, output torque, internal and exterior temperatures, case vibrations, etc. [2]. A considerable quantity of information about the system's state may be found in the vibration signature measured at the exterior surface or at any other appropriate location. To analyze the state of the rotor supported by ball bearings, extensive research was conducted. To forecast the rotor behavior at greater speeds, the inertia effects of the spinning pieces must be considered.

The modal and dynamical reaction qualities of structures were obtained by experimental study [3]. Shaft components used in rotor motors are particularly vulnerable to fatigue-induced transverse cross-sectional fractures. Early defect detection necessitates a robust vibration monitoring system. To find aspects of the system response that could be caused by the existence of a transverse fracture, local and global asymmetric crack models were used. It is demonstrated that the main response feature brought on by the insertion of a fracture is a 2x harmonic element of the system response [4]. When it comes to problem detection at high frequencies, accelerometers are more reliable than others.

When a fan's vibration signature drastically changes, several signal-processing approaches can be used to locate the issue [5]. The multi-rotor system's coupling is the cause of the misalignment. whatever the rotor speed, misalignment will produce a range of forces and moments at the couplings depending on the offset between the two rotors [6]. The focus of vibration monitoring systems was on predictive and preventive upkeep initiatives. Simple mathematical models were used to support several particular defects, including imbalance, excessive radial load, friction involving the rotor and the stator, fluid-induced vibrations, loose stationery and rotating parts, linked torsion/lateral vibration excitation, and rotor cracking [7]. Vibration monitoring and analysis are governed by several standards.

They facilitate data processing, measurements, vibration of machinery, and classifications [8]. The design suggests how many experiments should be conducted and how they should be conducted. The goal of parameter design is to discover the important factors and the factor values that are involved in the optimal performance of the process or product [9].

The purpose of the experiment was to determine the performance of gear pumps. Regression analysis and statistical techniques for results treatment are used to carry out the inquiry according to a precisely defined strategy. There is a functional link between the parameters, including gear normal pressure angle, oil temperature, revolution speed, pressure, and flow capacity [10]. Machining metal matrix composites is difficult as well as expensive. One of the key non-traditional machining techniques for complicated profiles and electrically conducting, challenging-to-machine materials is electrolysis machining.

The settings of the process parameters, such as voltage, feed rate, electrolyte concentration, and material removal rate were studied and determined by using Taguchi's experimental design method, orthogonal array, signal-to-noise ratio, and the analysis of variance are employed to optimize the process [11]. The influence of optimized machining places on the hole diameter and material removal rate is examined, including spindle speed, feed rate, and tool point. Using Statistical Software Minitab 15, the Taguchi-based approach is applied in conjunction with ANOVA (Analysis of Variance) and Coe (Design of Experiments) to achieve the best possible outcome [12]. The Taguchi technique is used to determine the ideal end milling process parameters for hard steel machining. ANOVA and the Taguchi approach match closely, and the most important parameter is identified. To calculate the values of tool wear and surface roughness, several regression models are created [13].

The creation of designs to examine variation and turning process optimization by the impacts of machining parameters using Taguchi techniques to enhance the quality of manufactured items. To determine the absolute maximum of each parameter, several experiments are conducted by changing one while holding the other two unchanged. With the aid of Minitab 15, a Taguchi orthogonal array is created, and the S/N ratio values are computed using three levels of tuning parameters. Because it requires fewer exams, the Taguchi approach is also anticipated to be an efficient method for optimizing different machining settings [14].

Choosing the right process variables is crucial to producing any product with the quality you want. The most crucial tool for robust design is Taguchi parameter design, which provides a methodical way to optimize a design for cost, quality, and performance. To determine ranges and combinations of turning parameters, this study outlines the Taguchi design of trials and orthogonal arrays [15]. The design of experiment (DOE) is a popular experimental or analytical technique that uses a methodical strategy to experiment preparation, data gathering, and analysis to statistically indicate the link between input parameters and output responses. DOE is a statistical method that uses experimental runs to create a theoretical framework [16].

EXPERIMENTATION

A vital piece of supply, the mill stand is powered by a motor that rotates at 2950 rpm. A flexible coupler connects it to the gearbox. Figure 1 illustrates how the shaft is supported by bearings. To use a vibrometer and a tri-axial accelerometer to gather velocities at various frequencies, bearing pedestals and vibration pads are supplied. These make it possible to monitor vibration in axial, vertical, and transverse directions. Whereas a tri-axial accelerometer gathers information simultaneously from all directions, a vibrometer receives reading at a single spot. All three orientations' dynamic vibration levels were measured. A multiplexer was linked to the tri-axial accelerometer's output. An FFT analyzer was attached to a multiplexer's return.

Fast Fourier Transform (*FFT*) analyzer was in turn interfaced with a computer for *ANFIS* modeling and analysis. Tables 1 to 3 give the vibrometer readings for critical machinery at different locations.

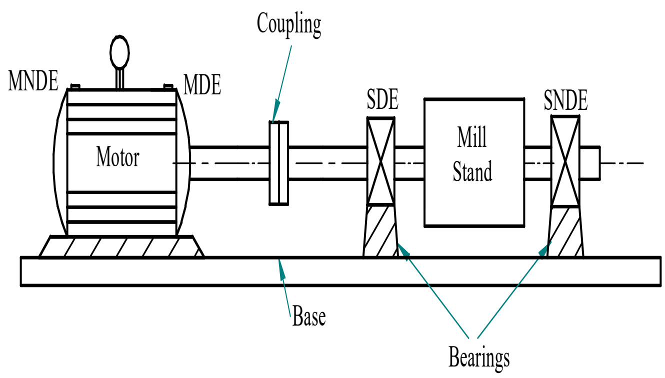

Figure 1. Experimental setup.

Table 1. Experimental results.

S. N.	F	MS 1XQV			AC 2XQV			FP *1x P H*		
		MNDE (P)			MNDE (P)			MNDE (P)		
		H	V	A	H	V	A	H	V	A
1.	1X	0.3	0.2	0.1	1.2	1.4	0.6	13.2	10.4	1.8
2.	2X	0.5	0.3	0.0	1.8	2.2	1.2	0.3	0.2	0.3
3.	3X	0.2	0.1	0.0	0.6	0.5	0.3	0.4	0.6	0.6
4.	4X	0.1	0.0	0.1	0.3	0.4	0.2	0.7	0.6	0.3
5.	5X	0.0	0.0	0.0	0.2	0.1	0.1	0.1	0.1	0.1
6.	6X	0.0	0.0	0.1	0.1	0.1	0.1	0.1	0.1	0.1

Table 2. Experimental results.

S. N.	F	MS 1XQV			AC 2XQV			FP *1x P H*		
		MDE (P)			MDE (P)			MDE (P)		
		H	V	A	H	V	A	H	V	A
1.	1X	6.7	5.5	0.0	5.2	5.1	0.2	1.1	1.0	2.2
2.	2X	0.4	0.2	0.1	6.3	5.8	1.5	0.8	0.5	0.2
3.	3X	0.0	0.0	0.1	4.8	0.4	0.4	0.3	0.6	0.6
4.	4X	0.1	0.0	0.0	1.5	0.8	0.2	0.3	0.3	0.3
5.	5X	0.2	0.1	0.2	0.1	0.2	0.1	0.1	0.1	0.2
6.	6X	0.1	0.2	0.0	0.2	0.1	0.2	0.2	0.2	0.1

Table 3. Experimental results.

S. N.	F	MS 1XQV			AC 2XQV			FP *1x P H*		
		SDE (P)			FS (P)			PDE (P)		
		H	V	A	H	V	A	H	V	A
1.	1X	5.4	5.5	0.5	7.6	6.8	5.7	4.0	2.6	3.4
2.	2X	8.6	5.4	0.1	2.0	1.8	2.0	1.0	1.0	1.5
3.	3X	4.8	0.0	0.3	0.3	0.5	0.4	0.9	0.8	0.0
4.	4X	0.1	0.2	0.0	0.2	0.3	0.1	0.7	0.7	0.0
5.	5X	0.1	0.0	0.0	0.1	0.2	0.1	2.4	1.4	1.0
6.	6X	0.4	0.1	0.3	0.1	0.1	0.1	1.4	1.1	1.2

Two measurement locations were considered for determining the vibration severity. One location each on the driver (*DE*) and driven end (*NDE*) was chosen for accurate identification of faults, in addition to the shaft drive end (*SDE*) at various harmonics.

TAGUCHI TECHNIQUE

It is used to optimize the design of the experiments, satisfying the two process objectives-

a. The number of trials must be determined and
b. The condition for each trial must be specified.

Identifying important responses, signal factors, noise factors, and control factors is an important task. A *P*-diagram of the vibration monitoring process is shown in Figure 2.

Noise factors represent the noise that is expected on the production floor. The noises cannot be controlled in the industrial environment, and they vary from time variant. Only the statistical characteristics, such as the mean and variance of noise factors can be known or specified but the actual values in specific situations cannot be known. The noise factors cause the response, *v,* to deviate from the specified target and lead to quality loss.

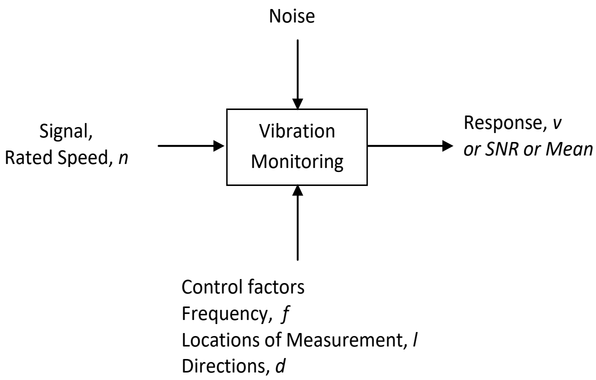

Figure 2. *P*-diagram of the vibration monitoring process.

The objective of the experiment is to maximize response, *v,* so that the condition of the machine is identified quickly. The ideal circumstances are determined so that the system response varies as little as possible under the effect of indeterminate variables like noise signals.

A quadratic loss function with "*larger-the-better type*" is used to obtain the maximum response, v_{max}.

The output velocity v, a quality A variable, maybe the vibration monitoring process's reaction. The rated speed, or n rps, is the speed at which spinning machinery is set to operate. Frequency (f), measurement locations (with a; P-NDE, Q-DE, R-SDE, FS, etc.), and direction of measurement (d) in the triaxial sensor (H, V, A) are control (or design) factors that should be adjusted at optimal values to enhance quality and reduce susceptibility to noise.

Design of Experiments (*DoE*)

The design suggests how many experiments should be conducted and how they should be conducted. Finding the factor values that end in the greatest performance of an operation or product is the goal of parameter control [9].

Construction of an orthogonal array (*OA*) requires the number of factors to be studied and the respective number of levels.

Table 4 gives the general linear model with mixed-level factors. It also mentions the optimum level (*L*) for each factor, along with justifications.

Table 4. General Linear Model.

S. N.	Design Factor	Type	Levels, L	Values	Justification
1.	Frequency, f	Fixed	$L_f = 6$	*1x, 2x, 3x, 4x, 5x, 6x*	The majority of faults can be detected within 6 fundamental frequencies.
2.	Location, l	Fixed	$L_l = 3$	*P, Q, R*	3 locations are enough for identifying combined faults.
3.	Direction, d	Fixed	$L_d = 3$	*H, V, A*	A triaxial sensor can sense only in 3 directions.

Each of the factor levels is of fixed type. The level for the factor frequency (*f*) is retained at 6, i.e., L_f=6 because most of the faults of rotating machinery surface within six fundamental frequencies or simple harmonics of vibration (1x, 2x, 3x, 4x, 5x, 6x). It is good enough to consider two locations of measurement (*NDE* – Non-driving end *&* *DE*– driving end) for most of the cases. However, for best results one more location (e.g., *FS* – first stage, shaft end – *SE*.) is added to make the level of the factor, *l* as 3 (*P – NDE, Q – DE,* and *R – SDE or FS...*), L_l = 3. There could be only three possible directions (horizontal-*H*, vertical-*V,* and axial-*A*) of measurement by a triaxial sensor, in each location. Hence the level of factor, direction, *d*, is fixed at 3 (*H, V, A*), i.e., L_d=3.

Several orthogonal arrays have been made by Taguchi to carry out the experiment design. Many experimental settings may be accommodated by each of the arrays.

The most suitable *L-18* is used to design an experiment to study three mixed-level factors. An orthogonal array (*OA*) design can be obtained as shown in Figure 2, by assigning factors, frequency *f,* location *l,* and direction *d,* as per Table 1, to the columns in *MINITAB* and choosing mixed-level factor design. OA enables a total of 18 runs (*N*) for analysis of variance (*ANOVA*). Assign factors to the columns, choosing mixed-level factor designs an *OA* to obtain a Taguchi design as shown in Figure 3.

Taguchi Design

Taguchi Orthogonal Array Design

L18(6**1 3**2)

Factors: 3
Runs: 18

Columns of L18(6**1 3**6) Array

1 2 3

Figure 3. Output of *OA* design.

A total of 18 runs (*N*) of the *OA*, with the specific combinations of parameters shown in Table 2, enables response analysis and analysis of variance (*ANOVA*) of the experiments conducted as per the combinations. Noise factors are excluded simply because they are not controllable in the industrial environment, where the vibration measurements are made. It suggests the optimum or best run combination(s) for obtaining the maximum velocity response. The optimum combinations differ from case to case and are dependent on environmental conditions.

Orthogonal Array

Table 5 gives the orthogonal array for the different sets of combinations of various factors, obtained for the critical machinery, for optimum response, v_{max}.

Table 5. Description of experiment and statistics η.

Run	OA			Mill Stand		Air Compressor		Feed Pump	
	f	***L***	***d***	***v***	***η***	***v***	***η***	***v***	***η***
1.	*1x*	*P*	*H*	0.3	–10.46	1.2	1.58	<u>13.2</u>	<u>22.41</u>
2.	*1x*	*Q*	*V*	<u>5.5</u>	<u>14.81</u>	5.1	14.16	1.0	0.00
3.	*1x*	*R*	*A*	0.5	–6.02	5.7	15.11	3.4	10.63
4.	*2x*	*P*	*H*	0.5	–6.02	1.8	5.11	0.3	–10.46
5.	*2x*	*Q*	*V*	0.2	–13.98	<u>5.8</u>	<u>15.27</u>	0.5	–6.02
6.	*2x*	*R*	*A*	0.1	–20.00	2.0	6.02	1.5	3.52
7.	*3x*	*P*	*V*	0.1	–20.00	0.5	–6.02	0.6	–4.44
8.	*3x*	*Q*	*A*	0.1	–20.00	0.4	–7.96	0.6	–4.44
9.	*3x*	*R*	*H*	4.8	13.62	0.3	–10.46	0.9	–0.92
10.	*4x*	*P*	*A*	0.1	–20.00	0.2	–13.98	0.3	–10.46
11.	*4x*	*Q*	*H*	0.1	–20.00	1.5	3.52	0.3	–10.46
12.	*4x*	*R*	*V*	0.2	–13.98	0.3	–10.46	0.7	–3.10
13.	*5x*	*P*	*V*	0.0	–80.00	0.1	–20.00	0.1	–20.00
14.	*5x*	*Q*	*A*	0.2	–13.98	0.1	–20.00	0.2	–13.98
15.	*5x*	*R*	*H*	0.1	–20.00	0.1	–20.00	2.4	7.60

16.	*6x*	*P*	*A*	0.1	–20.00	0.1	–20.00	0.1	–20.00
17.	*6x*	*Q*	*H*	0.1	–20.00	0.2	–13.98	0.2	–13.98
18.	*6x*	*R*	*V*	0.1	–20.00	0.1	–20.00	1.1	0.83
Observations									
Opt combination (*OA*)				*1xQ V*		*2x Q V*		*1x P H*	
Opt parameters (*MEA*)						*1x Q V*			

It can be observed that, a combination of the three design factors which yield maximum response, v_{max} are based on the measurements of vibration behavior and can be obtained from the *OA*. This set of design factors is designated as optimum combination (*OC*). The optimum parameters (*OP*) were obtained from the η *ANOVA* conducted based on the set of experimental results as per *DoE*. In general, the levels of the factors of both the *OC* and *OP* match well.

Table 6 gives the set of optimum levels of the factors, obtained for the critical machinery, for optimum response, v_{max}.

Table 6. Optimum levels design factor.

Design Factor	**Mill Stand/Feed Pump**		**Air Compressor**	
	OC	***OP***	***OC***	***OP***
Frequency, *f*	*1x*	*1x*	*2x*	*1x*
Location, *l*	*Q*	*P*	Q	*Q*
Direction, *d*	*V*	*H*	*V*	*V*

Out of the three critical machineries, for both mill stand and feed pump, *OC* and *OP* match well and suggest a distinct set of factors frequency *1x*, location, *P,* and at the direction, *H.* The matching and common set of *OC* and *OP* for the mill stand and feed pump are *1xQV* and *1xPH* respectively. However, in the case of air compressor*, OC* and *OP* suggest a distinct set of factors *2xQV* and *1xQV*, respectively.

However, the optimum set of parameters and their corresponding maximum responses v_{max}, highlighted in Table 2, can be considered for the purpose of assessing the machine condition.

Study of Main Effects

The primary objective of the design is to determine the best or optimum level for each factor. The optimum level for a factor is the level that gives the highest value of η in the experimental region. The experiments are characterized by the trial conditions (v) of each run. There are two main effects (or the responses), which are considered for determining the significant parameters of the experiment. They are signal-to-noise ratio (*SNR*) and mean effects (*ME*). The terms and expressions related to response analysis are given in Table 7.

Table 7. Statistical terms of response analysis.

S. N.	**Terms**	**Symbol**		**Illustration of η Expressions**	**Significance of Factor**
		SNRA	***MA***		
1.	Ratio	η	μ^*	$\eta = -10\,log_{10}\left\{\frac{1}{N}\sum\frac{1}{v^2}\right\}$	Characteristic Response.
2.	Max	η_{max}	μ_{max}	η_{max}	Most influential level.
3.	Min	η_{min}	μ_{min}	η_{min}	Least influential level.
4.	Delta	Δ_η	Δ_μ	η_{max}- η_{min}	Rates- 1, 2, ...
5.	Rank	r_η	r_μ	1, 2 or 3	Importance.

Note: $^*\mu = v$, in the case of MA; Significance level, α (Confidence level 95%) [9].

The meaning of the various terms used for the response analysis is described herein.

SN Ratio *(η)*

The quality characteristic signal-to-noise ratio (η), to obtain the maximum response, *v,* is determined according to the equation-

$$\eta = -10\log_{10}\left\{\frac{1}{N}\sum\frac{1}{v^2}\right\} \tag{4.1}$$

Where, N = Number of Measurements and v = Measured value of response.

Max *SNR* (η_{max})

η_{max} gives the greater significant level at a significance level α.

Min *SNR* (η_{min})

η_{min} gives the smaller significant level at a significance level α.
Delta (Δ_η)
Delta of *SNR* is given by, $\Delta_\eta = \eta_{max} - \eta_{min}$
It rates the factors and assigns ranks.
Rank (r)

The order of Δ_η suggests the rank. The factor with maximum Δ_η is assigned the highest rank (1) and vice versa. The factor with $r = 1$, is considered most important. The results of *ME* analysis for *SNR* (η) and mean are as shown in Figures 4 and 5.

Main Effect Analysis for Signal-to-Noise Ratios

Taguchi Analysis: Velocity versus Frequency, Location, Direction

Response Table for Signal-to-Noise Ratios

Larger is better

Level	Frequency	Location	Direction
1	-0.5570	-26.0797	-10.4756
2	-13.3333	-12.1919	-22.1919
3	-8.7917	-11.0625	-16.6667
4	-17.9931		

Figure 4. Typical results of *ME* analysis for *SNR*(η).

Main Effect Analysis for Means

Taguchi Analysis: Velocity versus Frequency, Location, Direction

Response Table for Means

Level	Frequency	Location	Direction
1	2.1000	0.1834	0.9833
2	0.2667	1.0333	1.0167
3	1.6667	0.9667	0.1833
4	0.1333		
5	0.1000		
6	0.1000		

Figure 5. Typical results of *ME* analysis for means.

The optimum parameters for the experiment are frequency *1x*, location *P* and direction, *H,* maximum response, and V_{max}. The optimum parameters for the experiment are frequency *1x*, location *P* and direction, *H,* give maximum response, v_{max}.

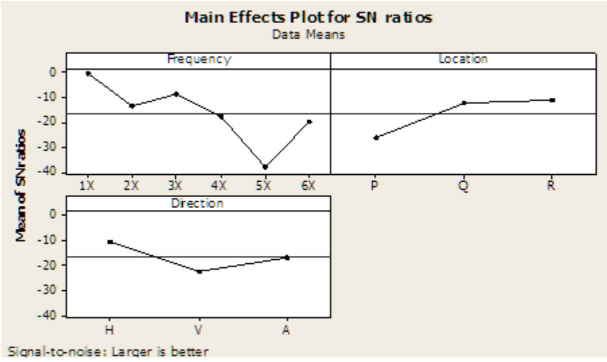

Figure 6. Main effects plot for SN ratios.

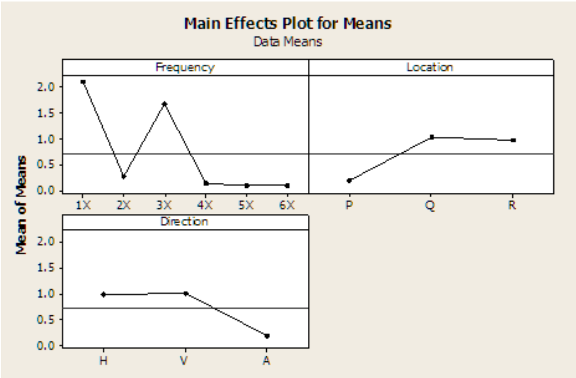

Figure 7. Main effects plot for means.

From the S/N plot (Figure 6) it is noticed that frequency is the significant factor and from the mean effect plot (Figure 7) it is observed that all the top points are optimized points at frequency 1X, position Q, and at vertical direction vibration is minimum. (Only within this range of values is vibration minimal).

Analysis of ANOVA

ANOVA technique for estimating error variance and for determining the relative importance of variance factors of typical cases of *SNRA*. *ANOVA* of the three critical machineries, mill stand, air compressor, and feed pump were conducted and the results are given in Table 8.

Table 8. Results of *ANOVA* for η of critical machineries.

S. N.	Statistics	Mill Stand		Air Compressor		Feed Pump		Recommended Range
		η	Comments	η	Comments	η	Comments	
1	$SeqSS_{max}$	2400.1	f*	2486.69	f*	944.20	f*	*Factor max value*
2	$AdjMS_{max}$	480.0	f*	497.34	f*	188.84	f*	*Factor max value*
3	MS_e	331.7	High &>>0	24.38	Low & 0 <<	62.13	Low & 0 <<	*≈ 0 (+ value)*
4	F-value (max)	1.45	F_p	20.40	F_p	3.74	F_p	*Predominant factor*
5	Δ_{max}	37.436	Rank1 &f*	30.284	Rank1 &f*	22.0642	Rank1 &f*	*Significant factor*
6	S-value	18.212	Bad (>η_{max})	4.93723	Better	7.8823	Relatively better	*Model* *< Lower S-value: better*
7	*RS* %	57.91	Relatively poor fit	93.20	Best fit	75.06	Better fit	*Fit* *0: Scatter 100: Best*
8	*AdjRS* %	10.57	Poor	85.56	Good	47.01	Normal	*Prediction* *0: Poor 100: Best*
9	P-value	0.305	>α: H_0 accepted	0.000	<α: H_0 rejected	0.071	>α: H_0 accepted	*α =0.05*

	(min)							*>α: H_0 accepted* *<α: H_0 rejected*
10	*P%*	*38.06*	*f**	86.66	*f**	47.37	*f**	*Factor max value*

Note: * – Significant Factor; Hypothesis: H_1- Maximum Response, v; H_0 – Null hypothesis.

The following observations can be made based on statistics of variance factors listed.

$SeqSS_{max}$ of factor frequency, in mill stand (=2400.1), air compressor (=2486.69), and feed pump (=944.20) is highest compared to the remaining factors, and hence frequency, *f* is significant in all the three cases.

$AdjMS_{max}$ of factor frequency, in mill stand (=480.0), air compressor (=497.34), and feed pump (=188.84) is higher than the remaining factors, and hence frequency, *f* is important.

MS_e in Mill Stand (=331.7)>> 0, whereas in air compressor (=24.38), and feed pump (=62.13) are 0<<. Hence *η* error variance is greater in the mill stand compared to the other two machineries.

The f-value of factor Frequency, in mill stand (=1.45), air compressor (=20.40), and feed pump (=3.74) is higher than the remaining factors, and hence frequency, *f* is significant.

Δ_{max} of factor frequency in mill stand (=37.436), air compressor (=30.284) and feed pump (=22.0642) is higher than the remaining factors. Hence, Frequency *f* is ranked as 1, in all three cases.

Since *f* is the most significant factor, the experiments must focus on the vibration response for assessing the behavior.

S-Value < η response values indicate a better fit. For mill stand *S*-value (=18.212) is > η (i.e., >η_{max}=14.81) response values the fit is bad. *S-value* for air compressor (=4.9372<η_{max}=14.16) and feed pump (=7.8823<η_{max}=22.41) are < η response values, which indicate relatively better fits. The fits represent the performance of the model.

RS percentage for mill stand (=57.91%), air compressor (=93.20%), and feed pump (=75.06%) are > 50%. It shows the fitted values are equal to the observed values and the model is good.

AdjRS percentage for mill stand (=10.57%), air compressor (=85.56%), and feed pump (=47.01%). The *RS* of the mill stands being < 50%, showing the poor prediction for air compressor Whereas the *RS* for the rest is> 50%, leading to good prediction of response values, *η* and hence *v*.

P-values for mill stand (=0.305) and feed pump (=0.071) are higher than α (=0.05) and hence it accepts the H_0 hypothesis. The *P-value* of air compressor (=0.00) is <α (=0.05) and hence it rejects the H_0 hypothesis.

P% is the maximal for factor in all the machinery and hence frequency, *f* is significant.

From the above study, it can be noticed that *ANOVA* analysis shows Frequency is significant and predominant in all case studies.

FFT Vibration Analysis

Vibration amplitudes of the mill stand measured at three different locations using *FFT* and tri axial accelerometer are given in Tables 9, 10, and 11 and the corresponding readings are plotted in Figures 8, 9, and 10.

Table 9. *FFT* analysis of mill stand at *MNDE* (*VSC* : 4.5 mm/s).

S. N.	Freq. *f*		Velocity (mm/s)		
	x	rpm	v_H	v_V	v_A
1	0.5	808	0.50	0.20	0.30
2	1.0	1616	5.96	5.90	0.99
3	1.5	2424	0.00	0.00	0.10
4	2.0	3232	2.42	2.17	0.50
5	2.5	4040	0.30	0.20	0.20
6	3.0	4848	0.90	0.70	0.60
7	3.5	5656	0.50	0.80	0.40
8	4.0	6464	0.98	0.60	0.40
9	4.5	7272	0.30	0.20	0.10
10	5.0	8080	0.60	0.30	0.20
11	5.5	8888	0.60	0.10	0.20
12	6.0	9696	0.40	0.20	0.10
13	6.5	10504	0.30	0.20	0.10
14	7.0	11312	0.00	0.00	0.10
15	7.5	12120	0.00	0.00	0.00
16	8.0	12928	0.65	0.45	0.26
17	8.5	13736	0.60	0.89	0.65
18	9.0	14544	0.30	0.00	0.10
19	9.5	15352	0.00	0.00	0.00
20	10.0	16160	0.20	0.10	0.10

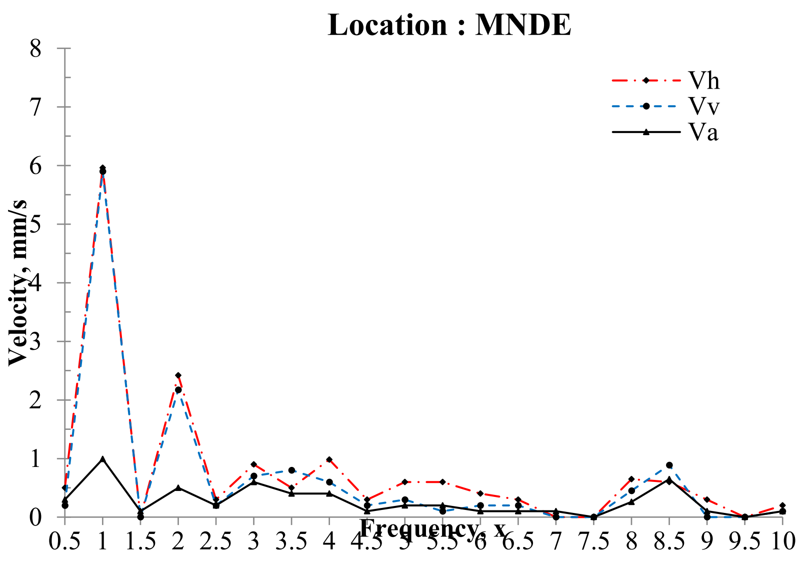

Figure 8. Rotor behavior at *MNDE.*

It can be observed from Figure 8 that the successive predominant velocities, *1x* velocities v_H (= 5.96 mm/s) and v_V (= 5.9mm/s) are in radial directions, hence the machine has forced unbalance or mechanical looseness-A.

Table 10 gives the measurements at the *MDE* location and Figure 9 gives the plot of the velocity behavior.

Table 10. *FFT* analysis of mill stand at *MDE* (*VSC*:4.5 mm/s).

S. N.	Freq, *f*		Velocity (mm/s)		
	x	rpm	v_H	v_V	v_A
1	0.5	808	0.70	0.60	0.50
2	1.0	1616	0.90	0.80	7.65
3	1.5	2424	0.20	0.20	0.10
4	2.0	3232	2.10	1.40	0.80
5	2.5	4040	0.60	0.40	0.20
6	3.0	4848	0.30	0.20	0.00
7	3.5	5656	0.20	0.30	0.10
8	4.0	6464	1.10	0.90	0.40
9	4.5	7272	0.30	0.20	0.10
10	5.0	8080	0.80	0.60	0.40
11	5.5	8888	0.00	0.00	0.20
12	6.0	9696	0.60	0.20	0.10
13	6.5	10504	0.40	0.20	0.10
14	7.0	11312	0.00	0.00	0.10
15	7.5	12120	0.00	0.00	0.00
16	8.0	12928	0.50	0.40	0.30
17	8.5	13736	0.30	0.20	0.10
18	9.0	14544	0.20	0.00	0.10
19	9.5	15352	0.00	0.00	0.00
20	10.0	16160	0.10	0.00	0.20

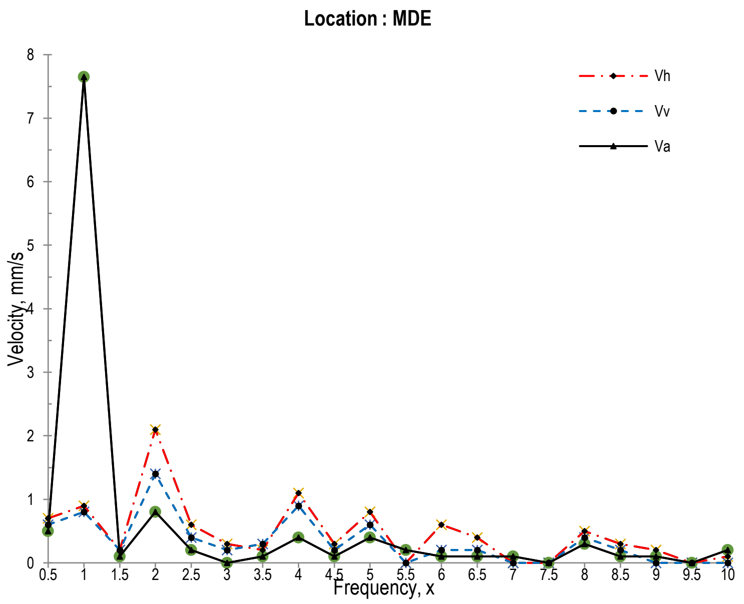

Figure 9. Rotor behavior at *MDE*.

The only predominant velocity, *1x,* is *Va* (= 7.65 mm/s) in the axial direction, hence the machine is in overhung rotor unbalance.

Table 11 gives measurement and Figure 10 gives the vibration behavior at *SDE.*

Table 11. *FFT* analysis of mill stand at *SDE* (*VSC* : 4.5 mm/s).

S. N.	**Freq, *f***		**Velocity (mm/s)**		
	x	**Rpm**	v_H	v_V	v_A
1	0.5	808	0.60	0.20	0.30
2	1.0	1616	6.45	3.46	2.56
3	1.5	2424	0.20	0.20	0.10
4	2.0	3232	7.25	3.25	2.10
5	2.5	4040	0.50	0.40	0.60
6	3.0	4848	5.90	1.45	1.60
7	3.5	5656	0.20	0.30	0.60
8	4.0	6464	1.20	1.30	0.50
9	4.5	7272	0.40	0.10	0.10
10	5.0	8080	0.80	0.30	0.20
11	5.5	8888	0.10	0.00	0.30
12	6.0	9696	0.60	0.30	0.20
13	6.5	10504	0.40	0.30	0.10
14	7.0	11312	0.10	0.00	0.10
15	7.5	12120	0.50	0.00	0.00
16	8.0	12928	0.20	0.60	0.50
17	8.5	13736	0.60	0.20	0.10
18	9.0	14544	0.40	0.00	0.10
19	9.5	15352	0.00	0.00	0.00
20	10.0	16160	0.20	0.20	0.10

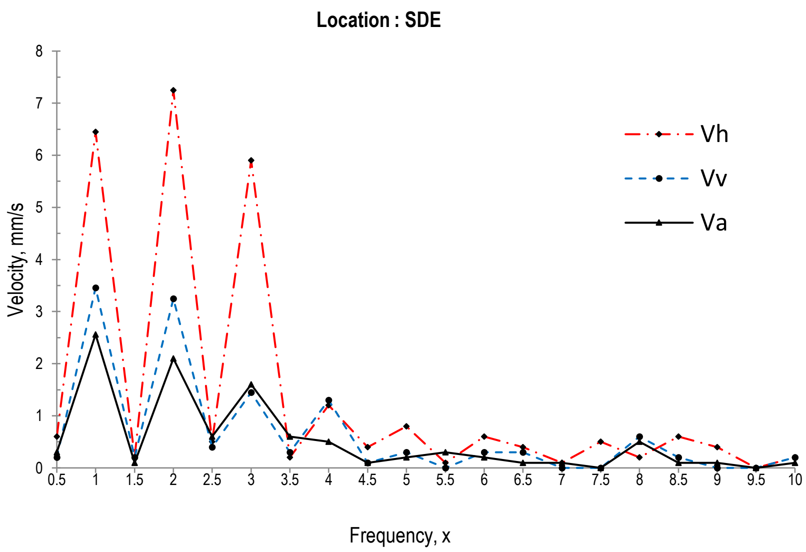

Figure 10. Rotor behavior at SDE.

The successive predominant velocities of *2x* (v_H = 7.25 mm/s), *1x* (v_H = 6.45 mm/s, and *3x* (v_H = 5.9

mm/s) are in radial direction. This feature clearly indicates parallel misalignment.

RESULTS AND DISCUSSIONS

The Taguchi technique emphasizes how essential it is to use the signal to noise to investigate response fluctuation, which eliminates quality characteristic variation caused by uncontrolled parameters. The idea that "the larger-the-better" applied to the qualities was the vibration level.

According to the major effect plots and analysis, the effect of process factors on the machinery's vibration level changes as frequency increases, location changes, and direction alters.

An objective, statistically based technique to identifying any variations in the mean performance of test item groups is ANOVA. By testing the mean square against an estimate of the experimental errors at confidence levels, ANOVA aids in the formal examination of the worth of all major components. ANOVA provided information on the model's acceptance as well as the relative importance and dominant factors controlling the vibration response.

The F test, which bears the Fisher's name, is a statistical technique used to determine whether design elements greatly influence the quality characteristic. The F-ratio, which is a ratio of the mean square error in relation to the residual error in the study, is commonly used to assess a factor's relevance.

The significance level has been released by the P-value. The impact on the rate of the process parameters on the rate of metal removal is expressed as a percentage (%).

The percentage numbers depict that the applied frequency, location, and direction have significant effects on the machinery vibration.

Fault diagnosis was carried out using both a vibrometer and an *FFT* analyzer. All the investigations tallied well with one exception, where the *FFT* was able to pick up more details, leading to a more accurate prediction of faults.

CONCLUSIONS

This paper has presented an investigation of the optimization and the effect of process parameters on the vibration behavior of the rotating machinery. A mixed-level factor *OA, L-18* was used in the design of the experiment. It helped in identifying the condition of the rotating machinery in one shot, adopting the optimum parameters for the experiment. The levels of importance of the process parameters on the vibration are determined by using ANOVA. The ANOVA approach revealed that frequency was the most effective parameter on vibration level, while location and motion were less effective. According to the findings, frequency had a greater influence on vibration level management than the second-ranking aspect. By analyzing the signal-to-noise (S/N) ratio, an ideal parameter combination for the highest equipment vibration was found. The experimental findings substantiated the applicability of the Taguchi approach, which is used to optimize process parameters and improve equipment performance in rotating equipment.

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