IOSR Journal of Computer Engineering (IOSR-JCE)
e-ISSN: 2278-0661,p-ISSN: 2278-8727, Volume 21, Issue 2, Ser. III (Mar - Apr 2019), PP 34-42
www.iosrjournals.org

Evaluation of Computational Predictive Maintenance Simulations in Multi-Machines Manufacturing

E. E. Jumbo[1], K.W. Kotingo[1], N. Olali[2], V. Zalizko[3]
[1] (Department of Mechanical Engineering, Niger Delta University, Bayelsa State, Nigeria)
[2.](Department of Mathematics/ Computer Science, Niger Delta University, Bayelsa State, Nigeria)
[3](Department of Enterprise Economics, National University of State Tax Service of Ukraine, Irpin, Ukraine)
Corresponding Author:E. E. Jumbo

Abstract: *Within the precincts of this study, predictive maintenance deals with a system's ability to recognize and report deviations in components to component's performance on a real-time basis. When this condition is embedded into the composite design of the manufacturing infrastructure, computational models can be developed to capture these deviations and convert them into raster codes for in-process behavioral parameter acquisitions and analysis. In this paper, we have demonstrated how predictive maintenance can be computationally deployed to interpret internal multi-machines transients and behaviors that deviates from standard conditions of performance as a result of wear, tear, shatter and vibration spurs. Thus, various manufacturing configurations were evaluated for consistency with the simulation model proposed in this study. Consequently, the computational syntax necessary for the proposed model have been shown to be direct logical performance derivativesof mathematical and statistical expressions used in representation of deployable machine readable codifications of the manufacturing process' behaviors. As expected, the generated simulation data and their derivative computations indicate the appropriateness of this model in various multi-machines configuration assembliesand were further projected to serve the decision making process with respect to maintenance prediction timing, machine capacity scoping, investment portfolio decision analysis and manufacturing capability and characterization.*

Keywords:*preventive maintenance, computational analysis and simulation, multi-machines availability, economic value dependence,opportunistic strategy, operability by inter-relativity, reliability determinants*

Date of Submission: 28-03-2019 Date of Acceptance: 13-04-2019

I. Introduction

It should be noted that equipment design computations significantly require inter and intra component analysis of stresses and tensions. The component to component inter-relationships established at the design phase is usually carried through to the operational stage and utilized to define the system's logic of operation. This characteristically form the basis for reliability assessments and evaluation anticipatory of machine work life conditionalities. Thus, operational mode of a manufacturing line, directly connote a factual condition of gradual component deterioration resulting from internal and external impacted stresses. This is referred to as wear and tear regime of a machine life cycle; and the resultant effect of this development, is a depiction of the original operational integrity referred to as its *reliability*;accordingly, a machine's reliability distribution is a function of its remaining useful life (RUL), design strategy and complexity, which varies with the corporate desires of the investor,environmental / legal compliances and reputational anticipations of the manufacturers.

In view of the foregoing the useful life of a machine or a manufacturing line-up of machines can be sustained for a longer time with an effective deployment of appropriate maintenance model or strategy[1], this feature could be more proactive if the appropriate maintenance model is not only recognized but also incorporated at the design phase of the venture.

Further, studies have shown that in-process and real time process data acquisition and analysis should be the basis for determination of maintenance type and characteristics[2]suggestive of condition-based maintenance (CBM) strategy,[2,3]which largely depends on cumulative operational data, analyzable into operational history of the plant in order to establish depletion tendency or likely maintenance directions. This situation is only achievable by means of extended periods of component monitoring and in-process surveillance; and implies that data generated from this surveillance can further be utilized to carry out the required cost benefit analysis of the chosen method. Thus, the maintenance-in-design inbuilt strategy has to be verified for applicability by effective comparison with other known models and appropriate deployment of cost benefit analysis.

It should further be noted that in-process data acquisition is capital intensive but generally cost effective when comparison with maintenance-based on failure regime is conducted. This imply that the benefits expected from maintenance regimes that has embedded futuristic and deterministic maintenance programs results a trade-off in terms of near-optimum cost distribution relativity for a specified operations cycle[4]; this strategy thus revolves around condition monitoring of critical and non-critical components within the plant until their reliability is no longer guaranteed and they fail.

However, it should be noted that in a typical multi-system manufacturing set-ups, inter-related components fail at various points under different constraints and service conditions. In view of this situation, it has been suggested that condition-based maintenance is the most appropriate strategy[5]. Specifically, and in response to multi-machine manufacturing conditions, the use of CBM in multi-gear wear conditions have been properly investigated experimentally[6].

The foregoing thus imply that any applicable operational real-time data acquisition technique must be designed to capture multi-system depreciation initiators in the various forms of wear and as to predict their possible progression to components failure. This need, further underscores the inability of most investigations to venture into CBM strategies that consider multi system conditions, with integrated parameter optimization schemes for maintenance scheduling.

This means that maintenance is only possible when certain threshold operational limits are envisaged such the complexity of this model is definitive of benchmark comparison between initial and operational parameters. The advantage of this proposition is that multi-system component to component interactions can be theoretically and computationally analyzed within the limits of imposed operational constraints on the active components. Thus, indicative of end to end process configurations of components inter-relationships and inter-phase results that can be deployed to enhanceprediction of maintenance stages, within a machine's lifecycle.

Notwithstanding the foregoing, certain continuous running or operating plants such as cargo vessels or ship, bulky production lines, chemical and process plants, etc., are likely to experience higher cost in maintenance downtime as compared with actual maintenance cost[7].In such a circumstance, the cost of machine unavailability far outweighs the cost of maintenance[4,7]. This type of manufacturing strategy thus requires in-built real-time maintenance assessment condition that are designed to prompt the operator on the need for certain checks given the fact that,known parameter configurations have undergone some variable impacts, thus resulting a range of internal transient behaviors.

I. Opportunistic Maintenance Strategy in Combined Multi-Components System Conditions

Although Opportunistic maintenance policy is not new, the implication of this strategy in multi machines systems can be a manufacturing system novelty. In view of this position survey reported that between 1976 to 1991 maintenance models in multi-components situations largely utilize time-based strategies[8]. Predictively, this tendency has been subsequently maintained over the years of manufacturing advancement till present time. In view of this situation, this study observe that time-based maintenance strategies are better viewed as group maintenance strategies. Consequently, some notable work has placed these strategies into three identifiable subsets, namely;

(i) *Block-replacement policy:* This group of components are fixed[9] in the sense that their maintenance arrangement has joint trajectory where control limit indices are to be deployed.
(ii) *Indirect grouping policy:* This policy defines all the range of grouping of components for which average attribute determines the possible optimal policy[10]
(iii) *Grouping by economic value dependence:* This identifiable group of components rely on their economic values to the process. Which implies that if the component does not have comparative advantage to the entire process, its maintenance may not be within the range of well-articulated maintenance programs. Components in this range have been adequately summarized into stationary and dynamic grouping models[11].

In view of the foregoing arguments, it should be noted that under multi-components maintenance analysis, these grouping make relative sense. However, where multi-machine interface is the issue these maintenance models may not be appropriate. This implies that under situations of a downtime of a particular machine, in the array of machines, independent isolation of such a machine possess significant constraint on the operation of the entire system.

II. The Proposed Approach

This study thus proposes a combinatorial approach to maintenance on multi-machine situations, by advancing the idea that *combined preventive and corrective maintenancepolicy* as an opportunistic strategy for multi-machine arrangement would better support modern manufacturing systems design and application.

It should further be stated that the combinatorial maintenance arrangement proposed in this paper shall be discussed under the structural functionality of multi-machines operational conditions, considered as follows:

a)Multi-Machines Functionality by Structured Alignments

Machine functionality in modern manufacturing draws from the idea of *dependency and operability by inter-relativity*. In this regard, certain processes and machines are designed to loop into each other such that their operational independence is not feasible on account of their shared energy resources, process control strategy and many other crucial design contemplations. Be that as it may,the operational performance of these machines can be represented by a random variable X_i. Where $X_i = 1$, an individual machine in the loop has performed within its operational limit, at the specified time. However,in cases where performance of the machine is outside the limit but within the noted time; the process value and behavior of $X_i = 0$.

The foregoing implies that the random variable,$X_i$is a binary component of the machine performance and it is defined as;

X_i = {1, if machine *i*operates satisfactorily within time *[0, t]*
{0, if machine *i*fails to operate within time *[0, t]*

In the foregoing case where X_i is definable within binary contemplations, the operability of the machines as a joint system is determined by the binary random variable $\phi(X_1,X_2,X_3....X_n)$which are operational states of the machine and defined as;

$\phi(X_1,X_2,X_3....X_n)$ ={1, if machine *i*operates satisfactorily within time *[0, t]*
{0, if machine *i*fails to operate within time *[0, t]* ……… (1)

It should be noted that the quantity, ϕ is referred to as the structure function of the system and is definitively connotative of the *n-machines* random selection variable. In this regard, the operation of the manufacturing template under consideration is a function of its*n-machines* and characteristic operations under binary codes of 1 when the individual machine operates optimally and 0, when it does not. Under this consideration, it should be noted that the structure function ϕ is contemplative of a 2^n value, where the points within the value is either 1 where operation is optimal and 0, where it is not. The foregoing thus imply that manufacturing capabilities do not under this condition entail a passive activity situation of near optimality since it is either a yes or no situation.

b) Multi-variate Operability Functions of Multi-Machines Strategy

It should be noted that modern manufacturing entails advanced application of interactive technologies such as CAD, CAM and CIM. The import of these products and production enhancement technologies is the automation of the production process, which has been defined as the technology concerned with the application of complex mechanical, electronic and computer-based systems in the operation and control of production[12].

Thus, where high technology content is used to define the manufacturing program, then maintenance strategy for such infrastructure should also come within the ambit of such technology. The implication of this view, is that manufacturing strategies determine the nature and character of maintenance policies and conditions.

III. Multi-Machines Configurationin Series and their Reliability Determinants

Although many configurations have been discussed in available literatures, this paper shall evaluate and advance the proposed computational simulation approach under series multi-machines manufacturing conditions.

It is important to note that where manufacturing plants or machines are arranged under series configuration as shown below, such machines are placed ahead or below each other in terms of their structural logic of functionality.

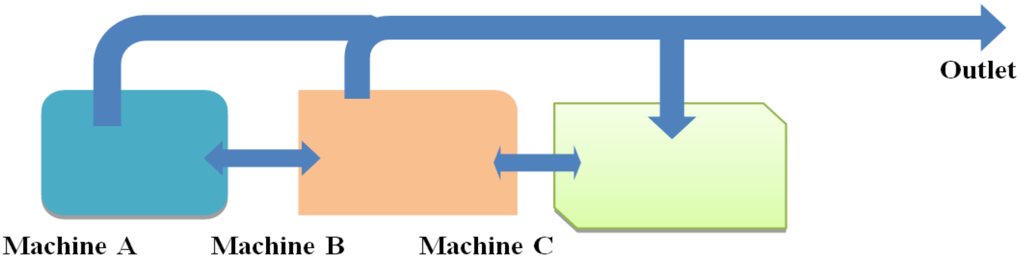


Figure1. Cyclic reversible process machines in series configuration

In this type of configuration as shown in Fig 1 above, where a machine fails, the entire interconnected system also fails. This implies that the manufacturing system performs optimally where all integrated machines perform under this condition. Relatedly, an integrated manufacturing strategy that adopts series configuration can be interactively analyzed as;

$\phi\ (X_1, X_2 \ldots. X_n) = X_1, X_2 \ldots. X_n = min\ \{X_1, X_2 \ldots. X_n\}$ …………….. (2)

Thus, equation (2) is relevant to the discussion on the basis that X_i is either 1 or 0. This makes the structure function assume the position of 1 if each machine X_i equals 1. In this line of argument assuming two machines are placed in series such that one is the engine (i.e. forcing function) and the other is the force transmission as shown in Fig 2 below.

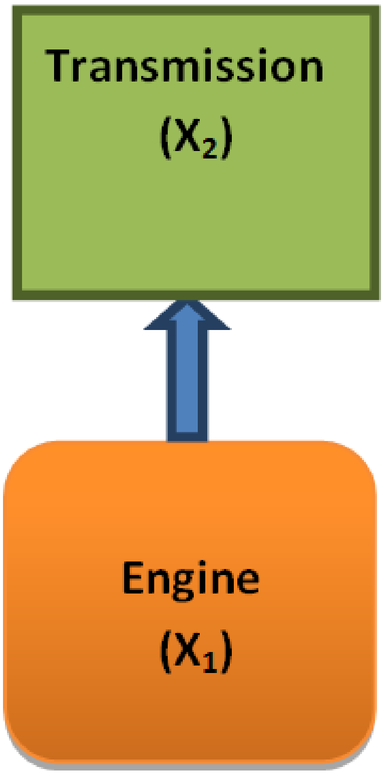


Fig. 2 Series configuration of $\phi(X_1, X_2)$

The foregoing Fig. 2 implies that the manufacturing strategy deploying machines or plants will perform satisfactorily or optimally if and only if, the machines in the assembly perform optimally. Thus, the failure of one is the failure of the entire manufacturing assembly. Implying that;

$\phi\ (X_1, X_2) = \phi\ (X_1) \pm \phi\ (X_2)$ ...………….(3)

Which means that; if the performance of the function is guaranteed,

$\phi(x_1, x_2) = X_1\ X_2$ ……………. (4)

and;

$\phi\ (1,1) = 1, \phi\ (1,0) = \phi\ (0,1) = \phi\ (0,0) = 0$ …………….(5)

It should be noted that equations (3), (4) and (5) forms the programmable *kernel* for automatic failure data acquisition agents. These agents are integrated as read-able sensors, relays and actuators designed to collect and store data in the most convenient manner for retrieval and processing when the machine satisfy state equation (4) and (5). Accordingly, this paper observesthat in advancedoperations and maintenance integrated systems, alarms are not triggered when the integrated machines perform optimally[13]. Consequently, this study finds that when sensor encodings indicate a deviation from pre-set configurations, alarms are triggered on for preventive maintenance decision and necessary action.

IV. Multi-Machines Configuration in Parallel and their Reliability Determinants

It should be noted that parallel machines configurations of *n-components* could be defined as a system that fails if all components fail. Conversely, this definition also applies where a system performs satisfactorily with all machines operating simultaneously. Thus, parallel machines configuration utilizes the practice of redundancy where some machines are designed or incorporated into the manufacturing system to enable it operate optimally in situations where an important machine fails. In view of the foregoing. The computational structure function for a simulation of parallel configuration of an integrated machine network could be programmed and coded in response to the following expression:

$$\phi(X_1, X_2 \ldots, X_n) = 1 - (1-X_1)(1- X_2) \ldots (1-X_n) = \max\{X_1, X_2 \ldots X_n\} \qquad \ldots\ldots\ldots\ldots\ldots 6$$

Accordingly, it has been observed that equation (6) is a complimentary redundancy expression indicative of the fact that each machine $X_i$is either 1 or 0 and thus connotes a sense of inter-related buffer production system. Thus, under this redundancy regime, the computational structure function assumes the definitive value of 1, if at least one of the machine X_i equals 1, due to a pre-programmed operational syntax, for preventive maintenance data acquisition[14]. Thus, in view of equation (6) two parallel machines placed by each other as shown in Fig 3 below;

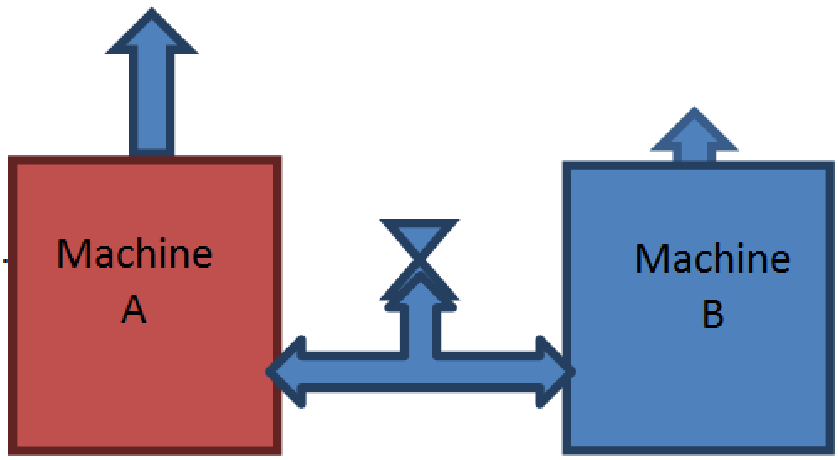


Fig. 3. Two Parallel Machines (One redundant)

As shown in Fig. 3above, an integrated system of two Machines A & Bthat have parallel configuration imply that although both are in operation at the same time, both simultaneously serve as a redundant machine to each other under the following programmable simulation syntax;

$$\phi(X_1, X_2) = 1 - (1-X_1)(1-X_2) = X_1 + X_2 - X_1 X_2, \qquad \ldots\ldots\ldots\ldots 7$$

and

$$\phi(1,1) = \phi(1,0) = \phi(0, 1) = 1, \phi(0,0) = 0 \qquad \ldots\ldots\ldots\ldots 8$$

In view of the foregoing, equations (7) and (8) proposes an automated data acquisition initiator that support a predictive syntax for a failure proofed manufacturing situation. Thus, data acquired during the machines optimal operational phase are also processed and stored in a proper retrievable manner. Thus, where this parallel system is in place, the efficiency of the system resulting improvement in the processes and functional capability of the integrated network of machines is significantly guaranteed under the redundancy regime of the configuration. As it can be seen in Fig. 2, the central control agent or valve can be activated on the event of failure of either of the machines, without necessarily shutting down of entire the system for maintenance.

V. CombinatorialMachine Coherency Configuration and their Reliability Determinants

This studyfurther proposes a network of systems utilizing a combination of parallel and series machines configurations. Under this system, the integrated machines operatean ***a***out of ***q*** sequence, whereby the series

configuration component is held as ***k***out of ***n***, and this applies for all instances where ***k***=***n***; and the parallel combination is also a***k***out of ***n*** sequence, where ***k = 1***.
The cumulative simulation syntax of the foregoing combined system indicates that if it is a ***k*** out of ***n*** system, then can it can be programmed to follow the syntax in equation (9)in an iterative manner;

$$\phi(X_1,\ X_2\ \ldots\ldots,\ X_n) = \begin{cases} 1, if \sum_{i=1}^{n} Xi \geq k \\ 0, if \sum_{i=1}^{n} Xi < k, \end{cases} \qquad \ldots\ldots\ldots\ldots 9$$

A Crucial view of the foregoing equation (9) indicate that it is expected that optimal performance of such integrated system defined by this equation would be dependent on the performance of one or more machines. Thus, general performance is coherently dependent on the combination strategy, such that the performance of one or more machines results an improved performance of the entire machines in that network. Mathematically it could be assumed that if $X_i \leq y_i$ for $i = 1, 2, 3, \ldots.. n$ then their structural function becomes;

$$\phi\ (y_1, y_2\ y_3\ \ldots\ldots\ y_n) \geq \phi\ (x_1, x_2, x_3\ \ldots\ldots\ x_n) \qquad \ldots\ldots\ldots\ldots..10$$

It is important to note that machines integrated under combinatorial coherency are more expensive but arelong term investment friendly due to their low operational downtimes[13].

VI. Simulation of Performance by Reliability Determination of Series Configuration

This study has observed that the structure function of an integrated system of *n-machines* could be assumed to be a binary random variable in the assumed values of *1*or *0*. Consequently, reliability of such as system can be expressed as;

$$R = P\{\phi\ (X_1, X_2, X_3\ \ldots\ldots\ X_n) = 1 \qquad \ldots\ldots\ldots\ldots 11$$

where P, connotes a cumulative probability as an operational value dependent on the structural function of the individual machines probabilities.
Further, where an integrated system of machines is placed in series, the reliability of such systems may be seen as either dependent or independent. However,if such a configuration is under series arrangement, the reliability of such a system could be stated as;

$$R = P\{X_1\ X_2 \ldots\ldots\ X_n = 1\} = P\{X_1 = 1, X_2 = 1\ \ldots\ldots\ldots\ldots\ X_n = 1\} \qquad \ldots\ldots\ldots\ldots..12$$

It should be noted that equation (12) could be simulated under conditional probability of dependent or independent variables; in that case equation (12) assumes some *cryptographic characteristics* that can be programmed and coded under the following syntax;

$$R = \underbrace{P\{X_1{=}1\}}_{a}\ \underbrace{P\{X_2{=}1|X_1{=}1\}}_{b}\underbrace{P\ (X_3{=}1|X_1{=}1,X_2{=}1}_{c} \ldots\ P\ \{X_n{=}1|X_1{=}1 \ldots.\ X_{n-1}{=}1 \ldots\ldots\ldots 13$$

A careful perusal of equation (13) indicate that the variables under *"a"* possess a reliability which depends on the probability that machine $\boldsymbol{X_1}$performance≤ **1**. While the variables under *"b"*indicate that an inter-relationship exist between machine $\boldsymbol{X_1}$ and machine $\boldsymbol{X_2}$ such that the functioningcan both affect each other due to interdependency. Thus, it implies that machine,$\boldsymbol{X_2}$ will perform optimally if and only if machine, $\boldsymbol{X_1}$also performanceoptimally. Assume that machine $\boldsymbol{X_2}$ is not well clamped on a horizontal base, the vibration conditionsensuing from the operation of machine,$\boldsymbol{X_2}$can result a low performance on machine $\boldsymbol{X_1}$. This same situation holds true for machines $\boldsymbol{X_3}$ in relation to machine $\boldsymbol{X_1}$ in the *"c"* term of equation (13).

It should be noted that in all three cases mentioned above, the analysis of evaluation of their conditional probabilities assumes very unconventional dimensions and as such difficult to be ascertained under this study.
However, where these integrated machines do not affect each other's performances, they could be said to be independent of each other and this narrows the reliability of such integrated machines to;

$$R = P\ \{X_1 = 1\}\ P\ \{X_2 = 1\}\ P\ \{X_3 = 1\}\ \ldots\ldots\ P\ \{\ X_n = 1\} \qquad \ldots\ldots\ldots\ldots..14$$

Based on the foregoing expression in equation (14), the integration ofmachinesX_1, X_2 and X_3 are independent of each other's performance, in which ease their reliability is a function of the probability distribution of the random variables $\boldsymbol{X_i}$ which can be established as;

$P\ \{X_i = 1\} = P_i$ ……………15

and

$P\ \{X_i = 0\} = 1 - P_i$ …………….16

In view of a system of integrated machines under independent performance regime, the reliability of such integrated system becomes a function of its probability distribution, such that;

$R = R\ (P_1, P_2 \ldots\ldots\ldots P_n)$ ……………17

VII. Reliability Based Performance Predictive Simulation

Under this section of the study, we shall depict some reliability based performance simulation, centered on the machines integrated configuration under discussion. Further, reliability prediction simulation under series configuration as stated earlier, reliability of integrated machines under independent series configuration can be expressed as;

$$R(P_1, P2, P3 \ldots\ldots, Pn) = P\{\phi\ (X1, X2, X3 \ldots\ldots., X_n) = 1\}$$ …………18

$$= P\{\ (X_1X_2X_3 \ldots\ldots., X_n = 1\}$$

$$= P\{\ (X_1{=}1, X_2{=}1, X_3{=}1, \ldots\ldots., X_n{=}1\}$$

$$= P\{X_1{=}1\}\ P\{X_2{-}1\} \ldots\ldots\ P\{X_n{=}1\}$$

$$= P_1P_2P_3 \ldots\ldots\ldots P_n$$ …………..19

The reliability equation (18) and its probability resultant equation (19), can be used to computationally simulate an integrated machine performance over a period of time where standard probability P of specific performance is determinable. In order to prove the operability of this proposed simulation, let'sassume that five machines are configured in series with predetermined individual reliability values of $X_1{=}0.98$, $X_2{=}0.97$, $X_3{=}0.95$, $X_4{=}0.93$ and $X_5{=}0.92$ respectively. Assuming these machines were designed to depreciate at an annual rate of X_1=0.02, X_2=0.03, X_3=0.04, X_4=0.03 and X_5=0.05 respectively. Thus, a reliability simulation in consonant with equation (19) for the determination of the system's reliability value after 5 years of optimal operational performance will produce table 1 below.

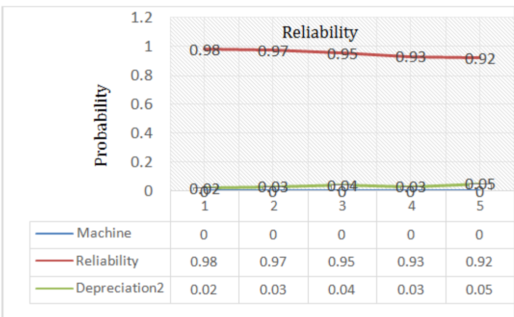
Table 1 Computational reliability prediction from machines depreciation rate

Machines	Year / Reliability	1	2	3	4	5	Depreciation Rate
X_1	0.98	0.015	0.030	0.045	0.060	0.075	0.02
X_2	0.97	0.022	0.045	0.067	0.089	0.112	0.03
X_3	0.95	0.029	0.058	0.087	0.117	0.146	0.04
X_4	0.93	0.021	0.043	0.064	0.086	0.107	0.03
X_5	0.92	0.035	0.070	0.106	0.141	0.177	0.05
Cumulative depreciation		0.122	0.246	0.369	0.493	0.617	

Table 2: Table of depreciation rate and reliability

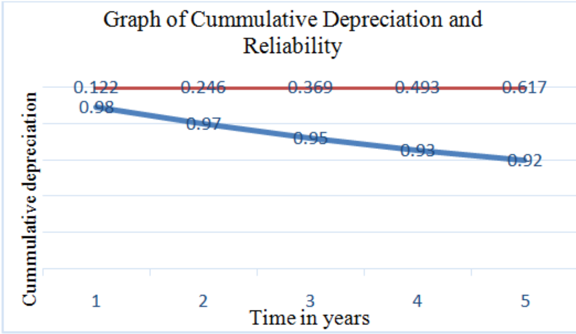
Year	Machine	Depreciation Rate	Reliability
1	X_1	0.02	0.98
2	X_2	0.03	0.97
3	X_3	0.04	0.95
4	X_4	0.03	0.93
5	X_5	0.05	0.92

Graph of depreciation rate and reliability



Depreciation/ Machine a,b,c,d,e (0)

Year	Reliability	Cumulative depreciation
1	0.98	0.122
2	0.97	0.246
3	0.95	0.369
4	0.93	0.493
5	0.92	0.617



In view of the foregoing, the iterative simulative computation syntax forTable 1 is as follows:
let,$R=P_1P_2P_3P_4P_5$

Where P=individual probability =0.98x0.97x0.95x0.93x0.92=0.77

This implies that thejoint or cumulative reliability of the machines which makes the system available for the sixth year operation is based on the probability of individual reliabilities of the machines under series configuration over the five years of consideration, i.e. $R = 0.77$after five years of deployment.
Consequently, using equation (19) to determine the reliability of each of the machines in the series configuration, we have the simulation syntax as;

$$R_{int} \cdot R_{ind} \cdot R \cdot Y \qquad \text{..…………20}$$

where,
R_{int}- reliability of all integrated machines in series configuration
R_{ind}- reliability of individual machines
R -rate of depreciation per annum
Y -the year under consideration

Thus, cumulative deprecation,could be resolved by using the expression,

$$D_c = \sum_{y=1}^{5} R(X1 + X2 \ldots \ldots Xn) \qquad \text{…………(21)}$$

where,X_n =5
then,

D_c= 0.122 + 0.246 + 0.0369 + 0.493 + 0.617 = 1.85%

Therefore, the cumulative depreciation, D_c = 1.85% of the original value of the configuration or 98.15% is the new value of the reliability of the machine, which is available for the sixth year deployment.

VIII. Discussions on the Model

In view of the foregoing, it can be established that 1.85% of the original reliability value of the machine have depreciated after five years of active optimal performance. The importance of this predictive model is that it can be performed manually by direct computation of the parameters defined in the various simulation equations and can also be programmed by writing coded computer programs and software that will interpret interface results from real-time recording implantsactivated with embedded data acquisition sensors and relays.

As could be seen from Table 2 and its consequent graph, increase in depreciation arising from machine wear and tear results lowering reliability factor and low availability of the machine for subsequent deployment. This means that machine availability reduces as depreciation negatively influences the reliability of the system. Further, from Table 3 and its resultant graph, it could be seen that increasing cumulative depreciation maintained a single line trajectory indicative of machine to machine interactions and shared reliability. This imply that individualistic reliability could have indicated an upward trajectory instead of a line trajectory as shown. It should consequently be pointed that reduction in reliability (as could be read from the graph) is as a result of the increasing cumulative depreciation which went down to the finding of 1.85% in five years of in-service simulation modelling.

The beneficial purpose of this model is that it is relevant in modern manufacturing conditions and can be used for facility scoping for determination of financial or economic value or worth of a current manufacturing concern. Further, in addition to supporting financial and investment decision making, this model can also enhance the manufacturing executive's machine deployment planning with respect to yearly production turn out in line with machine aging performance capacity.

Finally, this simulation model gives the maintenance engineer the sense of the internal condition of the machines, thereby enabling situations of statistical predictive maintenance on the ground that a perusal of Table 1, can quickly result an appropriate predictive maintenance decision in concrete terms of non-probable reliability values.

Acknowledgment

The authors appreciate the support of the leadership of the Department of Mechanical Engineering, Niger Delta University, Bayelsa State, Nigeria for unhindered access to the department's entrepreneurial based manufacturing facilities and the various machines maintenance records at the Advance Manufacturing Workshops of the Department.

References

[1]. Jardine, A. K. S., Lin, D. &Banjevic, D. (2006). A Review on Machinery Diagnostics and Prognostics ImplementingCondition-based Maintenance. Mechanical Systems and Signal Processing 20: 1483–1510.

[2]. Nandi S, Toliyat H.A. (1999). Condition Monitoring and Fault Diagnostic of Electrical Machines-A Review, *Thirty-Fourth IAS Annual Meeting*, vol. 1, Phoenix, AZ, USA, pp. 197–204.

[3]. Wang, H., Pham, H., Izundu, A.E. (2001). Optimal Preparedness Maintenance of Multi-Unit Systems with Imperfect Maintenance and Economic Dependence. Pham, H. (Ed.), *Recent Advances in Reliability and Quality Engineering*. *World Scientific, New Jersey*, pp. 75–92.

[4]. Baker, R.D. and Scarf, P.A. (1995). Can Models Fitted to Small Data Samples Lead to Maintenance Policies with Near-optimum Cost? *I.M.A. Journal of Mathematics Applied in Business and Industry* 6, p. 3-12.

[5]. Huang, R. Q., Xi, L. F., Li, X. L., Liu, C. R., Qiu, H., & Lee, J. (2007). Residual Life Predictions for Ball Bearings Based on Self-organizing Map and Back Propagation Neural Network Methods. *Mechanical Systems and Signal Processing* 21(1), 193–207.

[6]. Tian, Z., Zuo, M. J. (2009). Health Condition Prognostics of Gears Using a Recurrent Neural Network Approach. *IEEE Transactions on Reliability*. Accepted for Publication, 2010.USA.

[7]. Cho D., Parlar M. (1991). A Survey of Maintenance Models for Multi-Unit Systems. *European Journal of Operational Research* 51, p.1–23

[8]. Cho D., Parlar M. (1991). This paper is conducts a survey of the various contributions of practitioners dealing with practically optimized maintenance and parts replacement methods in the advancing field of multi-unit systems capabilities. It should be noted that this work discusses core areas of predictive maintenance, such as: machine interference/ repair models, group/ block/ cannibalization/ opportunistic models, inventory/ maintenance models, other maintenance/ replacement models, and inspection/ maintenance models thereby centralizing the core relevance of time-based maintenance based on some level of predictability.

[9]. Archibald, T.W., Dekker, R. (1996). Modified Block-Replacement for Multiple-Component Systems. *IEEE Transactions on Reliability* 45 (1), 75–83.

[10]. Van Dijkhuizen G, (2000). Maintenance Grouping in Multi-Setup Multi-Component Production Systems. In Ben-Daya M, Duffuaa S, Raouf A, (eds.) *Maintenance, Modeling and Optimization*, Kluwer Academic Publishers, Boston, 283–306.

[11]. Dekker R., van der Duyn Schouten F., Wildeman R. (1996). A Review of Multi-Component Maintenance Models with Economic Dependence. *Mathematical Methods of Operations Research* 45, 411–435

[12]. 12 Hegland, D. E., "Flexible Manufacturing-You Balance Between Productivity and Adaptability" Production Engineering, May 1981 p. 169-221

[13]. Batos P., Lopes L., Pires L., Application of Data Mining in a Maintenance System Failure Prediction in Safety and Risk Analysis. Beyond the Horizon found in Steen Bergen et al (Eds) 2014. Taylor and Francis Group, London, ISBN 978-1-138-00 23-7.

[14]. Hillier F.S. and Lieberman, G.J., Operations Research, CBS Publishers, New Delhi 2000, p.580-584