Industrial Engineering Letters
ISSN 2224-6096 (Paper) ISSN 2225-0581 (online)
Vol.8, No.4, 2018
www.iiste.org

Development of Simulation for Condition Monitoring and Evaluation of Manufacturing Systems

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Abstract
Equipment Condition Management used for predicting the performance parameters required for maintenance decision making was developed. This program predicts the state probabilities and maintenance action recommendation based the predetermined alert levels. The maintenance program software was developed from the derived stable state probability models using algebraic substitution and computation of the breakdown data and operational data of the MTTF, MTTR, λ and μ of these equipment/component(s) at PM and CM states with implementation algorithm. The models were derived using mechanistic modeling technique such that all the relevant variables of the reliability process were accounted for. Validation analysis of this simulation revealed its prediction accuracy of over 99%. Therefore, its use in the monitoring and evaluation of the health conditions of production systems remains very essential.
Keywords: Mechanistic model, process parameter, stable state probabilities, prediction algorithm, Equipment Condition Management

1.0 Introduction
It is important to state that industrial machineries and engineering systems are constantly improving, been characterized by significant technological changes (Funk, 2013). Therefore, improved equipment maintenance strategy is vital more than ever before to reduce unplanned equipment failures that can negatively impact on production and safety (Medjaher et al, 2012). For engineering systems, performing maintenance is essential. Early detection and correcting abnormalities are critical to prevent component or equipment malfunctions and performance degradation (Shreve, 1994). Mohamed (2011) stated that equipment monitoring and maintenance planning is among the most important problems faced by productive/service organizations. To this end, the industrial community in recent time, is concerned about critical systems and components, taking particular interest in their health analysis to ensure availability and reliability of the system with aims both to maximizing equipment uptime and to minimizing maintenance and operating costs. To achieve this, there is the need for a technique which can be used easily and quickly to predict the reliability of equipment. In addition, it is vital to monitor the degradation of equipment and components to keep equipment operating at full capacity and in top working condition and to prevent equipment breakdowns at an inopportune time.

It is worth noting that traditional maintenance policies include corrective maintenance (CM) and preventive maintenance (PM). With respect to existing maintenance technique, time-based maintenance (TBM) schedules are implemented to determine equipment replacement. The main assumption in TBM models is that the chance of a component failure depends entirely on the age of the component. This means that two components of same type and same age have the same failure rate, regardless of the events that have occurred during their operation or the manufacturing process (Suprasad and Hoang, 2006). Investigations conducted in several industries indicate that there is no direct relationship between equipment failure and equipment age in the majority of cases. Most failures are caused by events or conditions that occur during component operation and manufacturing processes. Therefore, maintenance decisions should be based on the actual deterioration conditions of the components as a result of effective monitoring. This way maintenance actions can be scheduled before failure and unnecessary process interruptions can be avoided resulting in decreased maintenance related costs. Well-defined maintenance system will ensure optimal performance of the machineries, improve the quality of goods and services and also satisfy customers' demands (Oke and Charles-Owaba, 2007 and Oberschmidt et al, 2010).

Considering this observed gap in equipment monitoring and maintenance planning, there is need for the development of a condition based maintenance (CBM) program which should be able to provide operators and maintenance personnel a full understand of plant machinery and equipment condition information to increase efficiency and aid in operation and proper maintenance planning. It is essential to monitor and track the current health state of critical components and machinery during operation to continue to ensure safe and productive operation and to prevent performance degradation and malfunctions which lead to substantial damage (Eshleman, 2002).

Continuing, it is known that machineries consist of multiple states and this can be modeled by Markov decision chains which is commonly used when precise measurements of the degradation states of the system cannot be obtained, and sometimes, it is a technical requirement since there is no need to work on every discrete value individually from an engineering practice viewpoint (Rommert, 2007 and Kurt and Kharoufeh, 2010). Instead, the degradation states are categorized into several deterioration levels. Markov chains consist of three important elements. First is the Probability transition matrix (π) which describes the switch between states. The second important element is the transition diagram, which is used to describe the model definitions; showing the possible switches between states according to the probability schematically. Lastly is the steady-state vector (P), which represents the total appearing percentage of a state in a Markov chain with a property that the sum of its elements in a row must be equal to one. In many applications of Markov chains the steady state probabilities are the main items of interest since one is interested in the long run behavior of the system. Chan and Asgarpoor (2006), Adoghe (2010) and Kadurumba (2015) have applied Markov chain procedure in modeling maintenance planning. With these transition probabilities, the steady state probabilities were computed as shown in equation 1.

$$\begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ . \\ . \\ . \\ P_n \end{bmatrix} \begin{bmatrix} \pi_{11} & \pi_{12} & 0 & 0 & 0 & \dots & 0 \\ 0 & \pi_{22} & \pi_{23} & 0 & 0 & \dots & 0 \\ 0 & 0 & \pi_{33} & \pi_{34} & 0 & \dots & 0 \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ 0 & 0 & 0 & 0 & 0 & \dots & \pi_{ij} \end{bmatrix} = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ . \\ . \\ . \\ P_n \end{bmatrix} \qquad (1)$$

The steady state probabilities are obtained by solving the equations $P\,\pi = P$.

Where: $P = (P_1, P_2, \dots, P_n)$, P_n are the unknown values and are the steady- state probabilities of the system states. To this end, the number of states in the state space, corresponds with the number of equations derived. π is the probability transition matrix.

Applying this formulation in maintenance planning, there may be data unavailability to estimate reliable probabilities especially for rare transitions. In addition, the robustness of the input variables to the stable state probabilities is not adequately quantified because they did not deal directly with breakdown data as obtained in the field that have direct influence on the equipment under monitor. Instead, assumed data values were used in their computation and analysis in compliance with the model restrictions. Considering these limitations observed, there is the need for a detailed model formulation for computing and analyzing the stable state probability of manufacturing equipment which will accommodate all necessary reliability data as obtained and also aid the identification of the health state and hitherto performance rate of equipment/component(s) of interest. This led to the development of the Condition Monitoring and Evaluation model by Nwadinobi (2017) using Stable State Probabilities of manufacturing systems, considering three health states of Normal state, Preventive maintenance (PM) state and Corrective maintenance (CM) state thereby implementing a realistic maintenance program.

Development of simulation for computation, prediction and optimization in engineering cannot be overemphasized as have been implemented by researchers in many areas of interest as reported (Hyun-Ah and Gyung-Jin, 2013; Marko *et al.,* 2013; Marko *et al.,*2014; Malozemov**,** 2015 and Bo *et al.,* 2015. Since these researchers and others in their works, showed elimination of computational rigors in implementation of mathematical formulations, to this end the objective of this work, is to develop a condition indication algorithm and simulation program **(**Equipment Condition Management) that will allow the prediction of the degradation states probability of an equipment/component(s) to enable better maintenance planning and decision making. This thereby reduces the tediousness involved in the implementation of the maintenance model manually as developed by Nwadinobi (2017) predicting state probabilities of manufacturing systems. The algorithm developed incorporates asset health information including failure event data and operating condition data into the model to have more effective and reliable predictions and real-time assessments of the current state of machinery health derived from operational data into the developed models to predict state probability of components of interest. This process assists in condition indication, reflecting levels of degradation which indicate the current state of the system.

2.0 Materials and Methods

The simulation **(**Equipment Condition Management) for implementing prediction of stable state probability from the performance models (Equations 2, 3 and 4) developed by Nwadinobi, (2017). The models, requiring a great deal of calculations require a program for easy handling. Java SE platform was chosen and used due to its flexibility on operational platforms and also good for numerical analysis. A computer program based on the developed formulation of the Markov Model for predicting Steady State Probability of manufacturing systems was implemented. The program was applied to a Bottle Filling machine identified as critical component in a Bottle filling line. This was carried out using data obtained from Line 1, 7up Boling Company, Aba Plant. This program allows one to assess the state probability of constituent components that make up a given system in order to know their health condition so that appropriate maintenance decisions can be taken and implemented.

Also, the sample result obtained from the computer program of the estimated steady state probabilities of the various health states of the sample equipment and the recommended maintenance action to be implemented as shown in figure 1.

$$\mathrm{P}_{1,2}(\text{NORMAL STATE}) = \frac{\mu_4\mu_3}{\mu_3\mu_4+\lambda_3\mu_4+\lambda_4\mu_3} \quad (2)$$

$$\mathrm{P}_3(\text{PM STATE}) = \frac{\lambda_3\mu_4}{\mu_3\mu_4+\lambda_3\mu_4+\lambda_4\mu_3} \quad (3)$$

$$\mathrm{P}_4(\text{FAILURE/CM STATE}) = \frac{\lambda_4\mu_3}{\mu_3\mu_4+\lambda_3\mu_4+\lambda_4\mu_3} \quad (4)$$

Where: $P_i(t)$ = probability that the system is in state i at time t, for i = 1,2; 3; 4, λ_4 = system failure rate, μ_4 = system repair rate, λ_3 = rate of system down for PM, μ_3 = rate of system PM performance. These models can predict system availability ($\mathrm{P}_{1,2}$), probability of system set for preventive maintenance(P_3), and probability of system failure (P_4). Although state probabilities indicate the deterioration trend of the targeted subject, the question of when will show that the targeted subject is in a failure situation, therefore, determination of the deterioration/failure limits is required. To this end, four reliability states deterioration are used in this work. These states are measured in terms of reliability index (values 10 to 0) as follows: Normal 1 (i.e., State 1: P $\geq$ 8.0), Normal 2 (i.e., State 2: 8.0 > D $\geq$ 5.0), PM State (i.e., State 3: 5.0 > D $\geq$ 3.0), and Unacceptable/ Failure (i.e, State 4: D < 3.0). These various alert levels attract four maintenance actions appropriate to each stage of degradation.

This Condition Monitoring and Evaluation process involves collection/acquisition of data from a system of interest, processing of extracted data of condition indicators is performed, diagnostics using discrete event model is performed to determine stable state probabilities of various degradation states, and finally a decision scheme is built on health condition detection and maintenance decision to be employed on the system. The algorithm in this work is implemented with Java programming language as part of a simulation application. The algorithm was then tested using plant process data as obtained from equipment of interest. This allows the coded algorithm to be studied and verified to determine how the algorithm should work and assessment of their effectiveness. The algorithm have proven to be effective. Figure 1, shows the flowchart of the developed algorithm.

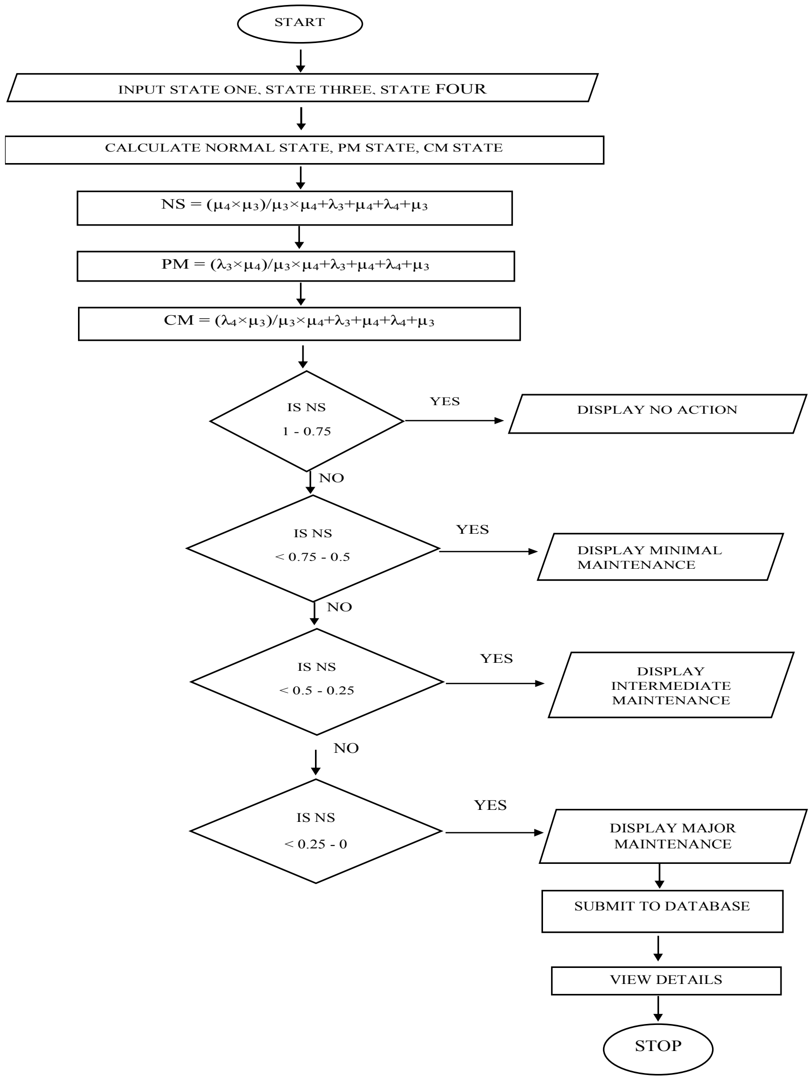


Figure 1: Flowchart for the computer program of the developed maintenance model

The implementation of this software requires operating system (OS) of Windows 2000 and above; with reasonable RAM size, disk space and high screen resolution. Its installation involves the pre-installation of the Netbeans IDE and Java applications, then import of the folder named 'Maintenance' to run the setup file inside the folder following the prompts to install the software. Launching this software after installation requires a double click on Netbeans shortcut icon on the desktop or single click the same on the window start menu (figure 2) to feature the window (main outlook) of the program environment (figure 3).

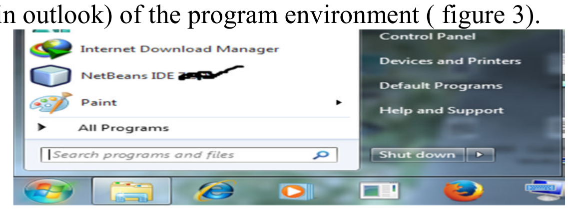


Figure 2: Icon for launching Equipment Condition Management

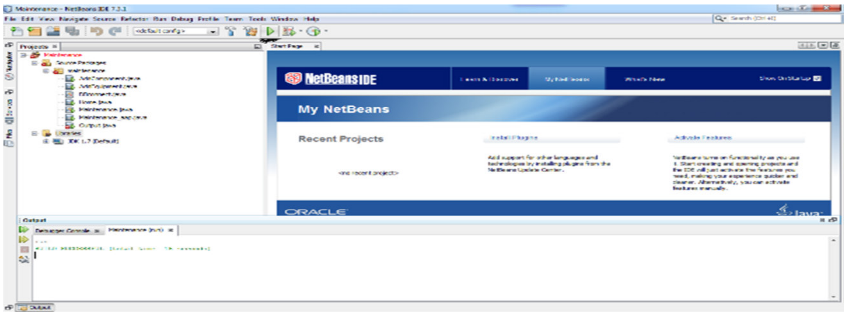


Figure 3: Main outlook of the program environment

On the clicking of the run icon (highlighted) in figure 3, the main program interface/ dialog box pops up by which operations are performed, it features the basic interface menu of the software as shown in figure 4, with about five sub-menu buttons such as: Maintenance, Add Equipment, Add Component, View Details and Exit, indicating five processes.

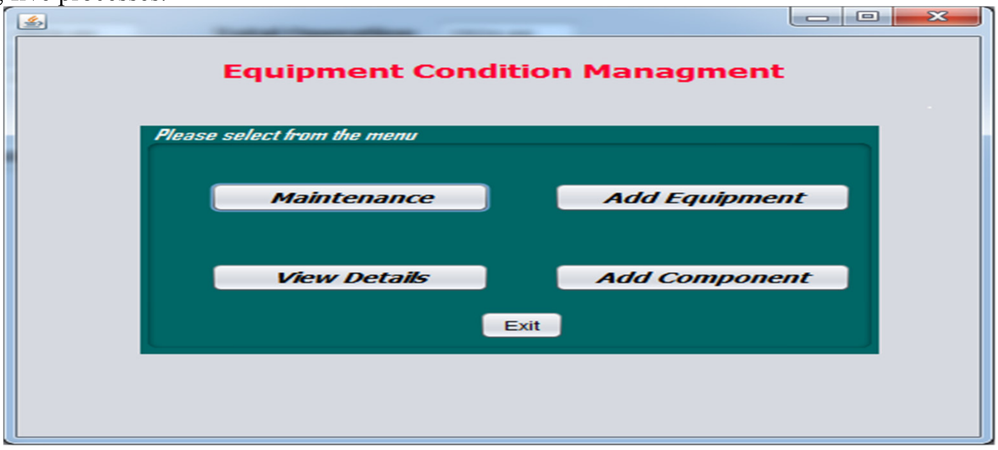
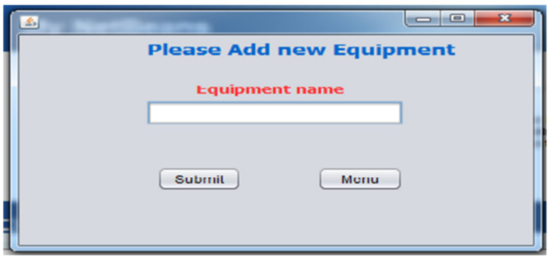


Figure 4: Main menu of the Equipment Condition Management



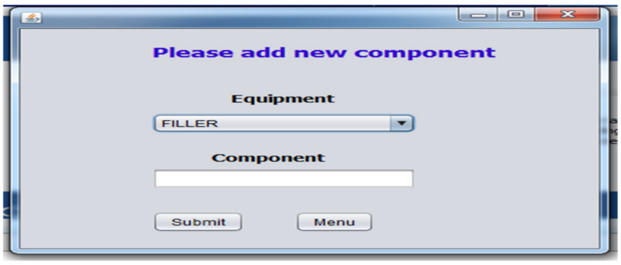


Figure 5: The Add Equipment menu box **Figure 6:** The Add Component menu box

The Add Equipment menu (figure 5) has option where the user inputs the name/identification of the equipment under study. The Add Component option (figure 6) consists of the selected equipment and provision for all the components that make up the equipment to be captured and submitted to the data base. View Details option is used for opening of existing data set for use or export records to other applications. Again is the Maintenance option that takes the user to the input form (figure 7) and Exit (to exit program).

The click on 'Maintenance' icon, brings up the input form and prediction result display as shown in figure 8. Prediction of health state of equipment under study requires operational parameters such as: Total downtime; Number of breakdowns and Total operation time for the period under review and for the three operational states considered. Using this program involves a click on 'Maintenance' icon to display a dialog box for entering the input parameter values desired. After inputting these values, click "CALCULATE" on the box, the request is processed. After processing, the program will compute values of the performance parameters, which are: Normal state probability, PM state probability and CM state probability (figure 8).

Prediction of these three performance indicators for a given set of operational parameters involves a click on CALCULATE button to run the computation and prediction of maintenance action based on the results of the stable state probability computation. From this result, one of four maintenance actions (No action, Minor maintenance, Intermediate maintenance or Major maintenance) set out is recommended.

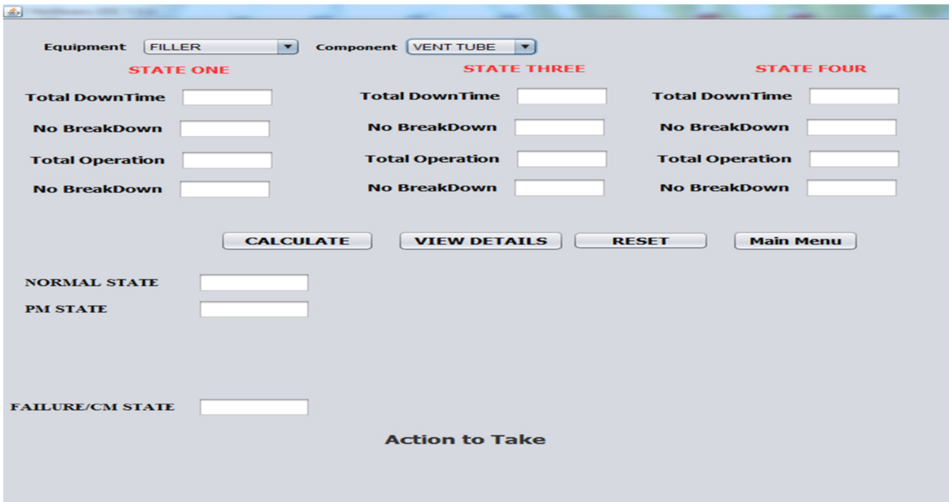


Figure 7: Input form and prediction result display

The Equipment Condition Management keeps record of all data it processes by detailing and presenting its saved input and generated data in an easy to comprehend tabular forms in Microsoft Access. The 'View Detail' icon on the menu box displays a table of input values for all the operational parameters sets saved in the program when clicked (figure 9) with the performance parameters. The predicted values of P_{NORMAL}, P_{PM} and P_{CM} for each of the parameter sets forms part of the table (figure 9) and are viewed by scrolling to the right-side of the table. The table form shown in figure 9 can be exported to Microsoft Excel for graphic display of values before printing when necessary.

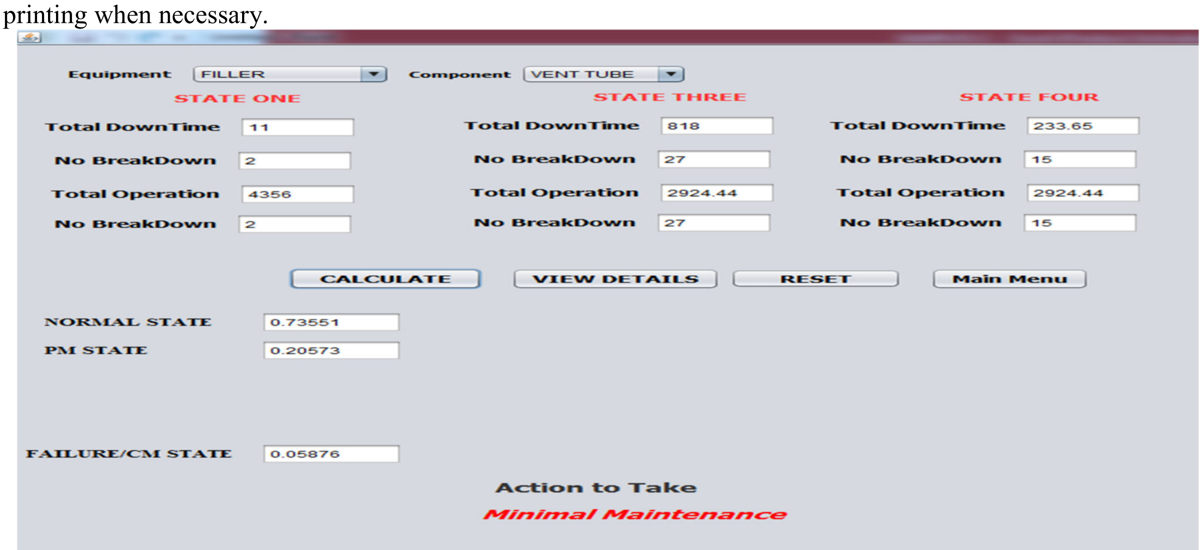


Figure 8: Computer program implementation sample

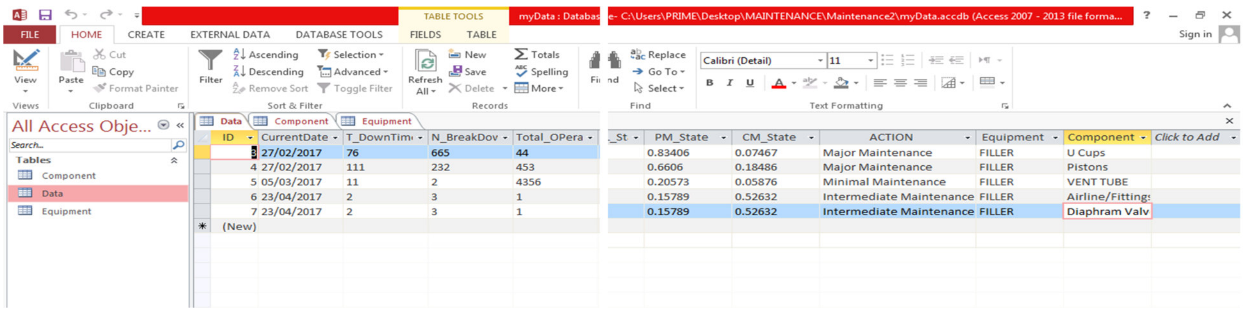


Figure 9: Display of saved data in database

Based on the decision algorithm presented in figure 1, the right time and maintenance action can be determined. The stable state probability prediction process using the Markov chain model as presented in, equations (2)-(4) is initiated after the data of $\lambda_i(t)$ and $\mu_i(t)$ have been updated. If the predicted state condition follows '*yes*' direction, then the decision of "do-something" is agreed upon (either do nothing, minor maintenance, intermediate maintenance or major maintenance). The maintenance action to take at any given time is based on predetermined alarm levels adopted in the work. The prediction capability of Equipment Condition Management was evaluated by comparing its predictions with the obtained results obtained by manual computation using the models from Nwadinobi (2017).

3.0 Results and Discussion

For components under study, the breakdown data and operational data were collected. The values of the MTTF, MTTR, λ and μ of these components at PM and CM states, were evaluated. These calculation results are as presented in table 1. By following the methodology explained above, Equipment Condition Management software was used to simulate the model using acquired data. Figure 10 presents the graphical result of the stable state probabilities of P_{NORMAL}, P_{PM} and P_{CM} as predicted by Equipment Condition Management software when operational parameters of the Bottle Filler components were inputted into it. Comparative evaluation results of the software predictions and the manual computation of the equipment investigated revealed about 99% prediction accuracy (Figure 11). This is expected because the simulation developed is base on mechanistic models that accounted for all operational and performance parameters of the manufacturing equipment.

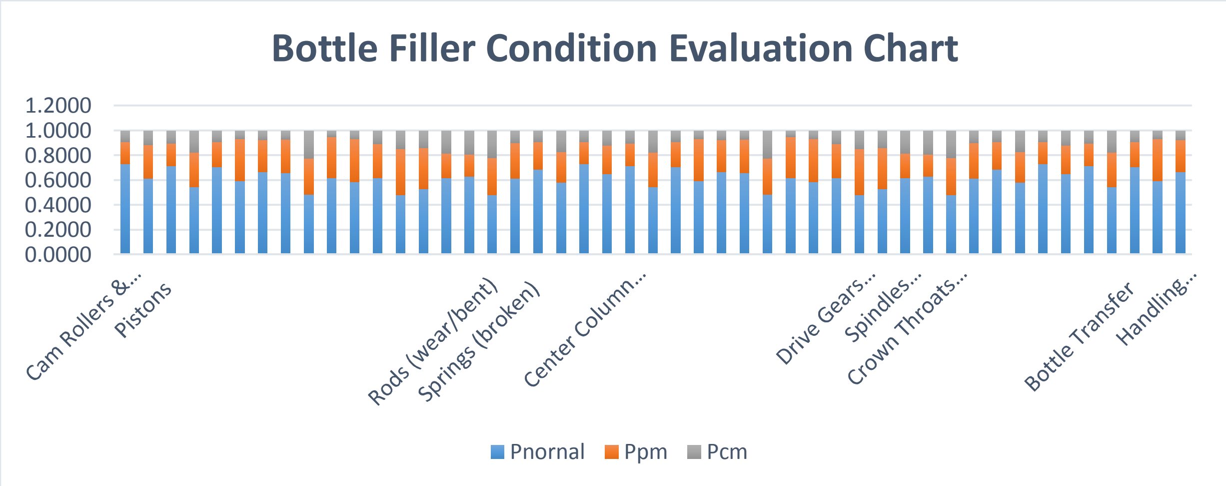


Figure 10: Predicted data plots associated with Bottle Filler components

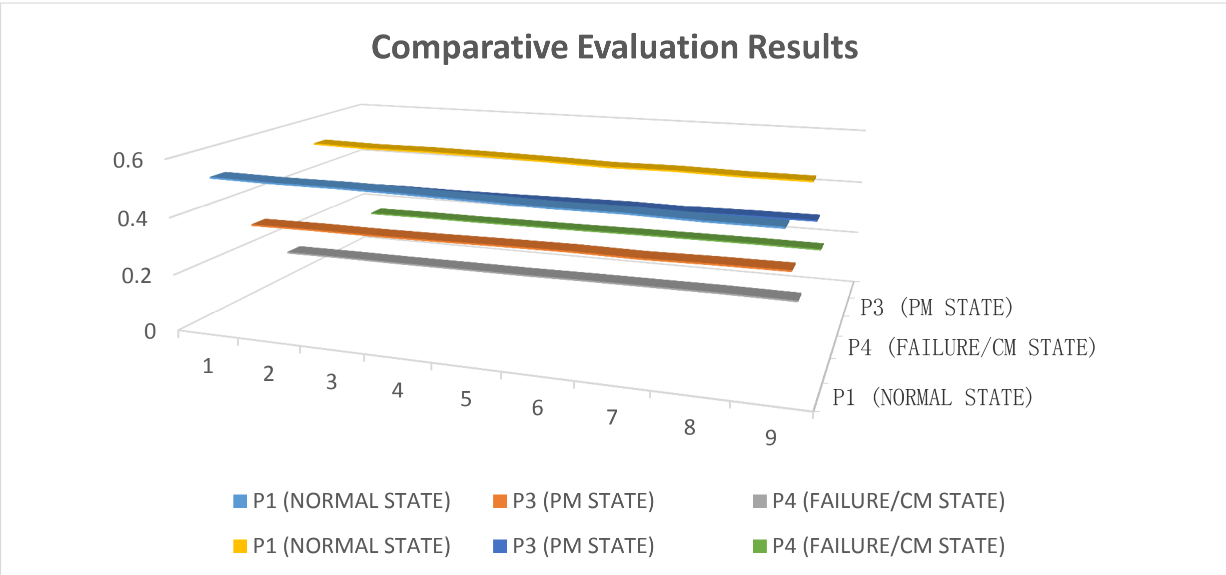


Figure 11: Comparison of the simulated and manual computation

Table 1: Maintenance Program (Meyer 78/18 Filler) Sample

EQUIPMENT/ COMPONENT	OPERATIOAL DATA						MAINTENANCE PLANNING PROCESS DATA				INPUT PARAMETER				OUTPUT PARAMETER/ RESULT			REMARK/ACTION
	PM STATE			CM STATE			PM STATE		CM STATE		PM STATE		CM STATE		P1,2 (NORMAL STATE)	P3 (PM STATE)	P4 (FAILURE/CM STATE)	REMARK/ACTION
	TOTAL DOWNTIME (DURATION)	NO OF BREAKDOWNS (FREQUENCY)	TOTAL OPERATIONAL PERIOD (DURATION)	TOTAL DOWNTIME (DURATION)	NO OF BREAKDOWNS (FREQUENCY)	TOTAL OPERATIONAL PERIOD (DURATION)	MTTR	MTBF	MTTR	MTBF	λ	μ	λ	μ				
Cam Rollers & Shoulder Bolts	818	27.00	2924.44	233.56	15.00	2924.44	30.2963	108.3126	15.5707	194.9627	0.0092	0.0330	0.0051	0.0642	0.7316	0.1773	0.0911	mM
U Cups	1098.85	20.00	3845.15	300.50	13.00	3845.15	54.9425	192.2575	23.1154	295.7808	0.0052	0.0182	0.0034	0.0433	0.6156	0.2706	0.1138	mM
Pistons	502.45	16.00	2016.59	156.96	9.00	2016.59	31.4031	126.0372	17.4395	224.0661	0.0079	0.0318	0.0045	0.0573	0.7190	0.1806	0.1003	mM
Airline/Fittings	1870.5	29.00	2361.01	644.50	16.00	2361.01	64.5000	81.4140	40.2809	147.5628	0.0123	0.0155	0.0068	0.0248	0.5440	0.2807	0.1753	mM
Guide Bushings/ Bumpers	834.64	23.00	3427.45	153.91	10.00	3427.45	36.2887	149.0196	15.3910	342.7450	0.0067	0.0276	0.0029	0.0650	0.7075	0.2054	0.0871	mM
Liquid Level Control (for leaks)	1286.32	18.00	2978.02	111.66	8.00	2978.02	71.4622	165.4453	13.9581	372.2519	0.0060	0.0140	0.0027	0.0716	0.5940	0.3396	0.0663	mM
Diaphram Valves (for sticking)	958.48	20.00	2877.71	139.81	10.00	2877.71	47.9240	143.8856	13.9807	287.7713	0.0069	0.0209	0.0035	0.0715	0.6688	0.2564	0.0748	mM
Rotherm Joint	1072.5	21.00	2858.23	145.28	11.00	2858.23	51.0714	136.1060	13.2068	259.8386	0.0073	0.0196	0.0038	0.0757	0.6604	0.2698	0.0698	mM
Sight Glass/Bowl Gasket	1689.69	23.00	2173.33	512.98	9.00	2173.33	73.4648	94.4926	56.9977	241.4812	0.0106	0.0136	0.0041	0.0175	0.4893	0.2876	0.2231	IM
Product Inlet Lines Seals	1608.45	24.00	3147.25	120.30	12.00	3147.25	67.0188	131.1356	10.0246	262.2712	0.0076	0.0149	0.0038	0.0998	0.6187	0.3317	0.0496	mM
Bowl Jacks (wear/binding)	1465.38	20.00	3068.12	142.50	10.00	3068.12	73.2690	153.4061	14.2498	306.8122	0.0065	0.0136	0.0033	0.0702	0.5882	0.3448	0.0671	mM
Outside Levers (adjustment/wear)	1204.52	22.00	3091.72	279.76	13.00	3091.72	54.7509	140.5326	21.5202	237.8244	0.0071	0.0183	0.0042	0.0465	0.6211	0.2720	0.1069	mM
Bushings/ O-Rings/Lever Spring	1905.66	20.00	2238.42	340.69	9.00	2238.42	95.2830	111.9208	37.8549	248.7129	0.0089	0.0105	0.0040	0.0264	0.4842	0.3691	0.1466	IM
Inside Levers (wear/bent)	1606.05	21.00	3270.47	331.21	10.00	3270.47	76.4786	155.7365	33.1214	327.0466	0.0064	0.0131	0.0031	0.0302	0.5328	0.3260	0.1412	mM
Vent Tubes (loose/bent)	996.89	25.00	2293.87	553.87	15.00	2293.87	39.8756	91.7548	36.9246	152.9247	0.0109	0.0251	0.0065	0.0271	0.6194	0.1976	0.1830	mM
Spreaders (damaged)	874.32	25.00	2251.71	336.76	9.00	2251.71	34.9728	90.0683	37.4181	250.1897	0.0111	0.0286	0.0040	0.0267	0.6333	0.1772	0.1896	mM
Rods (wear/bent)	2328.26	30.00	2464.09	1133.10	20.00	2464.09	77.6087	82.1363	56.6550	123.2045	0.0122	0.0129	0.0081	0.0177	0.4821	0.2993	0.2185	IM
Guide Bushings (wear/looseness)	1087.53	19.00	3174.18	259.69	13.00	3174.18	57.2384	167.0619	19.9765	244.1673	0.0060	0.0175	0.0041	0.0501	0.6182	0.2831	0.0988	mM
Springs (broken)	878.81	22.00	3254.56	145.92	9.00	3254.56	39.9459	147.9346	16.2132	361.6180	0.0068	0.0250	0.0028	0.0617	0.6900	0.2205	0.0895	mM
Shoe/Actuator (loose or binding)	942.13	18.00	2547.63	437.97	12.00	2547.63	52.3406	141.5351	36.4973	212.3027	0.0071	0.0191	0.0047	0.0274	0.5846	0.2448	0.1707	mM
Bottle Sensors (damage)	818	27.00	2924.44	233.56	15.00	2924.44	30.2963	108.3126	15.5707	194.9627	0.0092	0.0330	0.0051	0.0642	0.7316	0.1773	0.0911	mM
Timing Pins (loose or damage)	1098.85	25.00	3845.15	300.50	13.00	3845.15	43.9540	153.8060	23.1154	295.7808	0.0065	0.0228	0.0034	0.0433	0.6508	0.2288	0.1203	mM
Center Column (grease at overflow)	502.45	16.00	2016.59	156.96	9.00	2016.59	31.4031	126.0372	17.4395	224.0661	0.0079	0.0318	0.0045	0.0573	0.7190	0.1806	0.1003	mM
Main Bearing Seal (damage)	1870.5	29.00	2361.01	644.50	16.00	2361.01	64.5000	81.4140	40.2809	147.5628	0.0123	0.0155	0.0068	0.0248	0.5440	0.2807	0.1753	mM

4.0 Conclusion

Equipment and components condition can be determined through monitoring of condition indicators (state probabilities). The development of an improved maintenance algorithm described in this work combines traditional statistical techniques with evaluations of component state conditions. Such improved detection procedure can enable maintenance personnel to detect and possibly eliminate the causal conditions leading to breakdown, to better plan for maintenance and repairs, to order parts and schedule maintenance just-in-time, and to reduce the chance of equipment failure during operation. This would result in cost savings since components and machinery. Analysis of this software revealed that its predictions compares with the manual computation of performance variables by about 99%.

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