# Degradation Modeling To Predict the Residual Life Distribution of Parallel Unit Systems on Benchmark Instances

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***Abstract*-A manufacturing system often consists of multiple units as workcells with complex work systems to achieve the desired outcomes in an efficient and effective manner. Uncertain events such as machine down time or scheduled maintenance are unavoidable in any manufacturing unit. In this paper, we are trying to find the maximum workload of the remaining machines to fulfill the production requirements. To achieve this, a dynamic workload adjustment strategy has been proposed with dynamic upgradation of residual life distribution model. With parallel configurations and different benchmark instances the simulation experiments has been conducted to evaluate the degradation rate of different units. Results show that the proposed method is effective for finding the residual life of multi-unit systems.**

***Index Terms*—Residual life prediction, multi-unit systems, simulation, workcell.**

## I. INTRODUCTION

Manufacturing systems often consist of multiple units as workcells which operates individually or combine itself for achieving the desired objectives. Parallel configurations are most common multiple units that operate autonomously and concurrently to meet the system requirement. Due to unavoidable degradation process face by each concerned unit, while performing the operations it has been considered that one of the unit was failed.

If the degradation level of a unit exceeds its predestined threshold it has to be repaired and restored to its original state, thus it can resume to its previous mode of proper functioning. Consequently, during a unit failure of a parallel unit system, the remaining functional units have to be assigned with relatively heavier workloads for maintaining the system production. For example, considering the case of manufacturing systems, the maximum production rate of a machine is designed with higher than the traditionally allotted workloads to overcome the unexpected or natural events. The Federal Reserve reported that the U.S. fabricating industries are facing nearly 20% of average redundancy Otoo and Collins[14].

Plethora of literature is available for a single unit system particularly in case of degradation modeling and prognostic analysis. But, limited research can be find on statistical and stochastic models for identifying the degradation rate of the multi-unit system which is our current area of interest. Liu *et al.*, [11] present a methodology for constructing a composite health index for characterizing the performance of a system through the multiple degradation-based sensor data from the concept of a data-fusion model. The degradation model with nonlinear random-coefficient models, with degradation analysis and traditional failure-time analysis to obtain asymptotic efficiency is discussed by Lu and Meeker [12]. A time-scale transformation with Wiener process for assigning workloads randomly from one machine to another by accumulated decay modeling of a unit subjected to variable stress levels has been suggested by Doksum and Hóyland [6]. With two stochastic degradation models using real-time data from the units to update the model and estimate the RLD (Residual Life Distribution) by Gebraeel *et al.,* [8]. Martin [13], Fararooy and Allan [7], Dimla [5], and Thorsen and Dalva [15] provide survey of similar research in different applications like cutting tools, high-voltage induction motors, railway equipment, and machine tools. The union of former data with real time sensor-based data to update the degradation model and the RLD of the component, within a Bayesian framework has been recommended to incorporate the environmental effects by Bian and Gebraell [2]. Wang [16] suggested several assumptions of the random coefficients model as the operating time progresses the concerned device shows its degeneration of its working condition and the level of degeneration can be observed at any point of time. As the degradation signal reaches a predefined threshold, the device fails to operate normally. In the same manner, the degradation modeling of multiple units during the inter-dependent degradation processes has been considered by Bian and Gebraeel, [3]. Hao *et al.,* [9], concentrated on distinguishing unit degradation signals from sensor data, which involve miscellaneous documentation from many identical units in a composite system. From these results, it is identified that all these publications focus only on identifying or modeling the degradation of the units.

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We extended the stochastic degradation model of the instantaneous degradation rate of a unit, which was expressed as a function of the concerned workload in Hao *et.al.* [10], by taking into account the parallel configuration. In this paper, the unit degradation model with a linear stochastic differential equation (SDE) is adopted to capture the variation in the degradation process. Our objective in this research work is to determine the amount of workload given to the each unit in a unit time. To achieve this, with already existed parallel configuration with different benchmark instances, the analysis has been conducted with the proposed dynamic workload adjustment methodology. With this method, initially at each stage, through analyzing the real-time condition monitoring data, the posterior distribution has been updated. Based on this updated distribution, the RLD of each unit for a specific workload is calculated. Later, with the predicted residual life, we further propose an optimization framework to avoid the overlap of unit failures for individual units. With simulation analysis the degradation rate of different units has been evaluated with different benchmark instances.

The remaining sections of this paper is organized as follows: In Section 2 the problem formulation is detaield. The framework of Dynamic workload adjustment is detailed in Section 3. The description of the proposed methodology for unit degradation modeling and the prediction of residual life distribution is illustrated in Section 4. With case study, the real time scenario of complex systems in a work cell has been discussed in Section 5. Experimentation has been done and their results are depicted in section 6. Section 7 concludes the paper.

## II. PROBLEM DESCRIPTION

The parallel configuration is the most generally used design in the manufacturing units due to its effectiveness and flexibility to handle different tasks. In this paper, we consider parallel configuration as unit systems and it is shown in Fig. 1. It consists of $M$ units to execute the operations of same type where the arrival of each operation can be assigned to any unit to complete the task. A number of operations that are assigned to each unit in a unit time is defined by the control variable that needs to be determined in this paper. The maximum amount of operation of a single unit that is capable of performing in a unit time is defined as the "capacity" of that unit, which is denoted as $C_m$ of unit $m$. The actual amount of operations performed by each unit in a unit time is defined as the "workload," which is denoted by $w_m(t)$ for unit $m$ at time $t$. In other words, here the workload $w_m(t)$ is described as the control variable that needs to be determined in this paper. By default, we have the range of workload as $0 \leq w_m(t) \leq C_m$, for $m=1,2,\ldots, M$. If unit $m$ fails at time $t$, then $w_m(t)=0$. Here, the "throughput rate" of the system at time $t$, which is denoted by TH($t$) and is defined as the summation of with "capacity" (i.e., the maximum throughput rate) of the system at time $t$, is equal to $\sum_{m=1}^{n_u(t)} C_m$. Note that $TH(t) = \min\left[\sum_{m=1}^{\tilde{n}_u(t)} C_m, D\right]$, in which the "demand" is represented by $D$. When $\sum_{m=1}^{n_u(t)} C_m \geq D$, then $TH(t) = D$. When the demand is surpassed by the system's capacity, the system maintains the throughput rate that equals the demand. On the other side, when $\sum_{m=1}^{n_u(t)} C_m \leq D$, then $TH(t) = \sum_{m=1}^{\tilde{n}_u(t)} C_m$.

Assumptions:

(1) We have considered the degradation rate of a unit to be directly proportional to its workload. It means a unit functioning under a higher workload is assumed to degrade faster and vice versa.

(2) Only one type of operation is performed by the units, and the demand is considered to be constant.

(3) In this paper, the actual value of $\lambda_m$ is unknown and random. To capture the variation in the degradation processes due to material inhomogeneity and other manufacturing related uncertainty, we assume "unit to unit variability" to be widely adopted in this paper.

(4) Unit failure due to unsatisfactory quality of the performed operations is not considered in this paper, only its own degradation rate is considered.

(5) The operation of a product on a machine should not be interrupted until it is finished

### *2.1 Mathematical Modeling*

Minimization of Throughput time

$$Z = \frac{1}{n_u(t_x)} \sum_{m=1}^{n_u(t_x)} [\beta_{(m)}(t_x) w_{(m)}(t_x)\delta t + A_{(m)}(t_x)] \qquad (1)$$

subject to the following constraints:

$$\sum_{m=1}^{n(t_x)} w_{(m)}(t_x) = \min\left(\sum_{m=1}^{n_u(t_x)} w_m, D\right) \qquad (2)$$

$$w_{(1)}t_{(x)} \geq \ldots \geq w_{(n_u(t_x))}(t_x) \qquad (3)$$

$$0 \leq w_m(t_x) \leq C_m, \qquad \text{for } m=1,\ldots,M \qquad (4)$$

$$\frac{d_{i(m)}(t_x)}{w_m(t_x)} + R_{(m)}\delta t \leq \frac{d_{i(m+1)}t_{(x)}}{w_{(m+1)}(t_x)} \qquad \text{for } m=1,\ldots, n_u(t_x)-1 \qquad (5)$$


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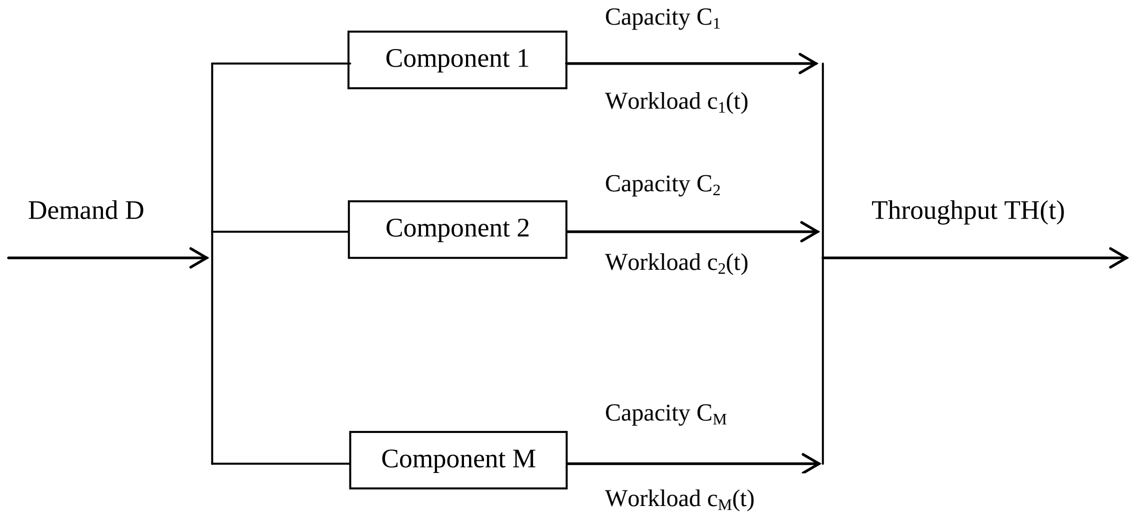


**Fig. 1** Parallel configuration

The objective function in equation (1) represents the throughput time of the system which ensures that on an average all units fail in the slowest pace, insight is somehow provided by its objective value on the system's health status in real time. Constraint (2) is to ensure that when the demand is less than the capacity of the system, then the throughput becomes equal to the demand. Conversely, when the demand is greater than the capacity of the system, the throughput is set according to the capacity of the system. Constraint (3) refers to the process of assigning higher workloads to units with more severe degradation status. Constraint (4) refers to condition or environment where the workload assigned to the machines is always less than the maximum capacity of the machines. Constraint (5) avoids the overlap of unit failures; that is, the difference between the predicted residual lives of any two units that will fail consecutively should be greater than the repair time.

## III. DEGRADATION MODELING FRAMEWORK

Degradation is a natural and unavoidable process that occurs gradually over a period, due to performing operations. It is observed that a unit is considered to be failed when the degradation level of the concerned unit surpasses a pre-defined failure threshold. In the paper, the pre-defined failure threshold is often determined by either industrial standards as detailed in Gebraeel *et al.* [8] or ideas based on data-driven approaches as explained in Liu *et al.,* [11]. A unit once considered to be failed must be repaired or replaced to bring back its original status before the restart. Although various other types of failures exist in reality, like catastrophic failure and cascading systems failure, in this paper, we have considered failure due to degradation. Nevertheless, we plan to have the above-mentioned failures in our future works. After degradation of a unit, the quality of the performed operations could certainly be affected. However, we have not included unit failure due to the deficient quality of the performed operations, but solely due to self-degradation of the units. Substantial knowledge on mathematical modeling and system configuration are required in developing the relationship between unit degradation and quality of operations.

### *3.1 Unit Degradation Modeling*

We interpret $A_m(t)$ as the amplitude of the degradation signal of unit *m* at time *t*. A generic degradation model is established where $A_m(t)$ is attributed as a stochastic differential equation given as

$$dA_m(t) = i_m(t)dt + dW_m(t) \qquad (6)$$

$$i_m(t) = \lambda_m w_m(t) \qquad (7)$$

$$dA_m(t) = \lambda_m w_m(t)dt + dW_m(t) \qquad (8)$$

where $i_m(t)$ is the instantaneous degradation rate, and $W_m(t)$ is a Brownian motion with variance $d_m^2 t$ *where* $d_m$ is expressed as the diffusion parameter. The instantaneous degradation rate $i_m(t)$ is proportional to the applied workload $w_m(t)$ where $\lambda_m$ is defined as the *degradation coefficient* of unit *m*.

## IV. CASE STUDY

A numerical case study has been taken in to consideration to investigate the performance of our proposed methodology. Having a hypothetical stamping system consisting of five identical stamping machines working in parallel configuration to fabricate parts and to obtain the degradation related parameters. In this study, the degradation related parameters such as degradation signals, instantaneous degradation rate and degradation coefficient are considered Chen and Jin, [4]. In order to capture the real

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world characteristics, parameters that are exploited to generate the degradation signals a unit of workload is considered as the quantity of parts taken in a unit time. Each individual machine has its own pre-defined mean of “degradation coefficient”, i.e., $\beta_1,\ldots,\ \beta_5$, which is equal to $5.97 \times 10^{-8}$ inch per part. Similarly, the diffusion parameter of the Brownian motion error of each machine, i.e., $d_1,\ldots,d_5$, is $2.03 \times 10^{-5}$ inch per unit time is considered. The failure threshold of each machine is identified as 0.004 to show the actual manufacturing settings. In this numerical case study, we assign a maximum workload of 1500 parts per day to each machine and the demand remains 6000 parts per day. Here, the decision epoch i.e. the unit time is considered as one day. If a machine breaks down during its ongoing operation, it has to undergo a repair process where a fixed amount of time that is not less than one decision epoch is taken. There may be a requirement of an excess repair time in terms of multiple of a day. If no more than one machine fails simultaneously, the demand can still be satisfied by the remaining machines.

## V. EXPERIMENTATION

The resources identified from the unit degradation modeling and their impact on the manufacturing system performance were examined. The performance measures of the system i.e., makespan is improved by simulation analysis. Here, we used a FlexSim simulation tool for conducting the above analysis. With screen shots the created environment of the problem description is shown in Fig.2. The simulation was conducted on a *PC* with Intel Corei3-4005U (107GHz, 3MB L3 cache) running under Windows 10 Professional operating system with 8 GB RAM. We considered two benchmark instances i.e. BM-1 and BM-2 for conducting the experiments. In BM-1 equal workloads were assigned to all functional units, whereas in BM-2 the workload assignments were given as random distribution. While assigning the workloads on the functional units with BM-2, different combinations of workload assignments are established, out of which random selection has been made for assigning the jobs on the considered configurations. The results were depicted and illustrated in Figs. 3(a-c) and 4(a-c) as Gantt charts.

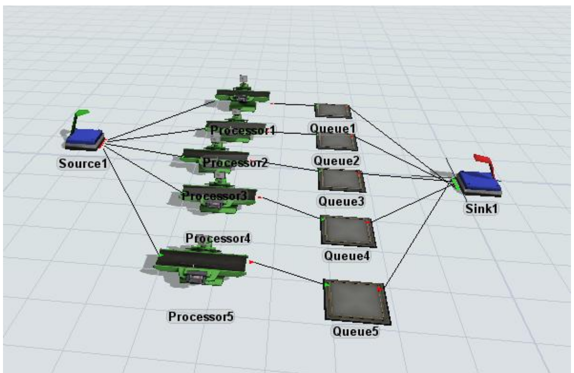
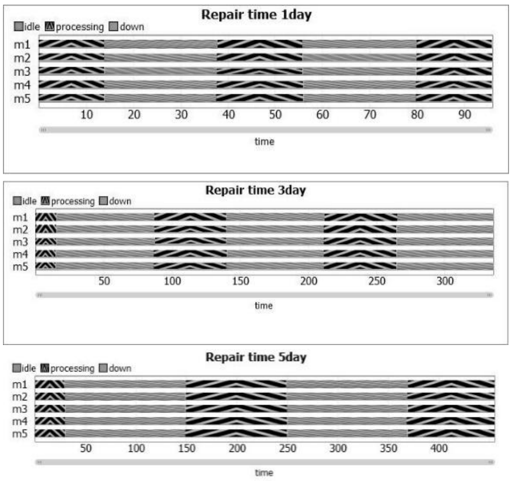



**Fig.2** FlexSim Parallel Configuration

Fig.3 (a-c) and Fig.4(a-c) presents results of simulation program i.e., for BM-1 and BM-2, for repair time 1,3 and 5 days. With obtained results we concluded that in all the three cases i.e. 1, 3 and 5 days, the workloads which were assigned to the machines were not fully completed which resulted in the loss of production. From Fig.3 (a-c) it can be observed that machines assigned with equal workloads lead to failing at the same period. Whereas in Fig.4 (a-c) the scenario was not the same. Here, as random arrangement of workload was done, the failure of machines was in a random manner which is reflected in the results. It is same for BM-1, where the workload was assigned to the machines was not fully completed, which lead to loss of production. But, when a comparison is done between BM-1 and BM-2 one can find that loss of production in BM-2 is less than BM-1.

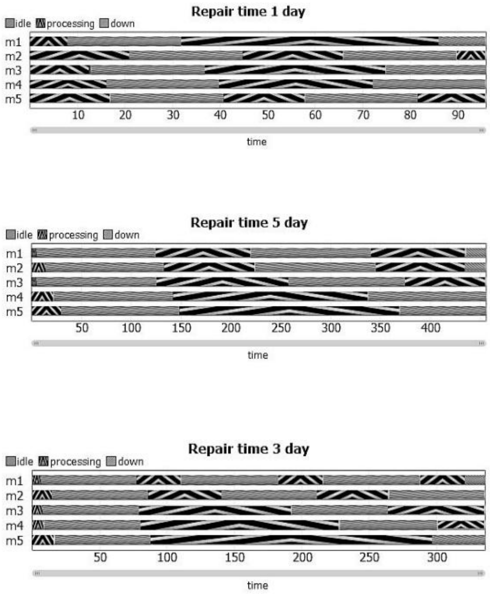



a)

b)

c)

**Fig. 3(a-c)** Benchmark- 1(Equally distributed arrangement of workload).




a)

b)

c)

**Fig. 4(a-c)** Benchmark - 2(Random arrangements of workload).

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## VI. CONCLUSION AND FUTURE WORK

In this paper, a dynamic adjustment of workload for degradation process controlling of each unit in real life adjustment of industrial units is considered. A Bayes scheme, which deals with degradation monitoring information in reality to upgrade the preliminary distribution of degradation coefficients, is taken in to account as a distribution. Thereafter, with dynamic workload assignment policy, the proposed method at each decision epoch the unit failures overlap is rectified. To demonstrate our method, we used a numerical study and make a contrast between two benchmark strategies, the former with evenly distributed and the later with randomly distributed workloads. The outcomes clarify that the proposed method can allow to find the throughput of the two benchmarks under different situations and also to prevent the overlap of unit failures and satisfying the demand of production. In the future work, with different configurations, the workload adjustments can be improved.

## REFERENCES

[1] Bian, L., and Gebraeel, N. 2012. "Computing and updating the first-passage time distribution for randomly evolving degradation signals." IIE Transactions, 44(11), 974-987.

[2] Bian, L., and Gebraeel, N. 2013. "Stochastic methodology for prognostics under continuously varying environmental profiles." Statistical Analysis and Data Mining: The ASA Data Science Journal, 6(3), 260-270.

[3] Bian, L., and Gebraeel, N. 2014. "Stochastic modeling and real-time prognostics for multi-component systems with degradation rate interactions." IIE Transactions, 46(5), 470-482.

[4] Chen, Y., and Jin, J. 2006. "Quality-oriented-maintenance for multiple interactive tooling components in discrete manufacturing processes." IEEE Transactions on Reliability, 55(1), 123-134.

[5] Dimla, D. E. 1999. "Artificial neural networks approach to tool condition monitoring in a metal turning operation." In Emerging Technologies and Factory Automation, 1999. Proceedings. ETFA'99. 1999 7th IEEE International Conference on (Vol. 1, pp. 313-320). IEEE.

[6] Doksum, K. A., and Hóyland, A. 1992. "Models for variable-stress accelerated life testing experiments based on wener processes and the inverse gaussian distribution." Technometrics, 34(1),74-82.

[7] Fararooy, S., and Allan, J. 1995. "On-line condition monitoring of railway equipment using neural networks."

[8] Gebraeel, N. Z., Lawley, M. A., Li, R., and Ryan, J. K. 2005. "Residual-life distributions from component degradation signals: A Bayesian approach". IiE Transactions, 37(6), 543-557.

[9] Hao, L., Gebraeel, N., and Shi, J. 2015. "Simultaneous signal separation and prognostics of multi- component systems: The case of identical components." IIE Transactions, 47(5), 487-504.

[10] Hao, L., Liu, K., Gebraeel, N., and Shi, J. 2015. "Controlling the Residual Life Distribution of Parallel Unit Systems Through Workload Adjustment." IEEE Transactions on Automation Science and Engineering.

[11] Liu, K., Gebraeel, N. Z., and Shi, J. 2013. "A data-level fusion model for developing composite health indices for degradation modeling and prognostic analysis." IEEE Transactions on Automation Science and Engineering, 10(3), 652-664.

[12] Lu, C. J., and Meeker, W. O. 1993. "Using degradation measures to estimate a time-to-failure distribution." Technometrics, 35(2), 161-174.

[13] Martin, K. F. 1994. "A review by discussion of condition monitoring and fault diagnosis in machine tools." International Journal of Machine Tools and Manufacture, 34(4), 527-551.

[14] Otoo, M., and Collins, J. 2010. "Industrial Production and Capacity Utilization: The 2010 Annual Revision". Federal Reserve statistical release, 39.

[15] Thorsen, O. V., and Dalva, M. 1999. "Failure identification and analysis for high-voltage induction motors in the petrochemical industry." IEEE Transactions on Industry Applications, 35(4), 810-818.

[16] Wang, W. B. 2000. "A model to determine the optimal critical level and the monitoring intervals in condition-based maintenance." International Journal of Production Research, 38(6), 1425-1436.

[17] Zhou, J., Djurdjanovic, D., Ivy, J., and Ni, J. 2007. "Integrated reconfiguration and age-based preventive maintenance decision making." IIE transactions, 39(12), 1085-1102.

[18] Zuo, M. J., and Tian, Z. 2006. "Performance evaluation of generalized multi-state k-out-of-n systems." IEEE Transactions on Reliability, 55(2), 319-327.