

January 01, 2005

Dynamic group maintenance policy in a smart sensor integrated flow-line manufacturing system

Surendra M. Gupta
Northeastern University

Srikanth Vadde
Northeastern University

Sagar V. Kamarthi
Northeastern University

Cheng Cui
Northeastern University

Recommended Citation

Gupta, Surendra M.; Vadde, Srikanth; Kamarthi, Sagar V.; and Cui, Cheng, "Dynamic group maintenance policy in a smart sensor integrated flow-line manufacturing system" (2005).. Paper 44. <http://hdl.handle.net/2047/d10014068>



Laboratory for Responsible Manufacturing

Bibliographic Information

Cui, C., Vadde, S., Kamarthi, S. V. and Gupta, S. M., "Dynamic Group Maintenance Policy in a Smart Sensor Integrated Flow-Line Manufacturing System", ***Proceedings of the 2005 Northeast Decision Sciences Institute Conference***, Philadelphia, Pennsylvania, March 30-April 1, 2005 (CD-ROM).

Copyright Information

Copyright 2005, Surendra M. Gupta.

Contact Information

Dr. Surendra M. Gupta, P.E.
Professor of Mechanical and Industrial Engineering and
Director of Laboratory for Responsible Manufacturing
334 SN, Department of MIE
Northeastern University
360 Huntington Avenue
Boston, MA 02115, U.S.A.

(617)-373-4846 **Phone**
(617)-373-2921 **Fax**
gupta@neu.edu **e-mail address**

<http://www.coe.neu.edu/~smgupta/> **Home Page**

DYNAMIC GROUP MAINTENANCE POLICY IN A SMART SENSOR INTEGRATED FLOW-LINE MANUFACTURING SYSTEM

Cheng Cui, Northeastern Univ., Boston, MA 02115, (617)-373-7635, cui.c@neu.edu
Srikanth Vadde, Northeastern Univ., Boston, MA 02115, (617)-373-7635, srikant@coe.neu.edu
Sagar V. Kamarthi*, Northeastern Univ., Boston, MA 02115, (617)-373-3070, sagar@coe.neu.edu
Surendra M. Gupta, Northeastern Univ., Boston, MA 02115, (617)-373-4846, gupta@neu.edu
(*Corresponding author)

ABSTRACT

Machine-tool breakdowns, both expected and unexpected, make it difficult to devise effective maintenance plans that do not adversely affect the performance of a manufacturing system. This work presents a heuristic maintenance grouping algorithm which takes the machine-tool failure information provided by smart sensors into account to come up with condition-based preventive maintenance plans that does not severely affect the manufacturing system operations. Studies on the simulation model of a flow-line manufacturing system integrated with smart sensors indicate that grouping of maintenance actions increases the uptime efficiency, boosts the production rate, reduces the maintenance cost, and decreases the production loss.

INTRODUCTION

Machine-tool failures are caused by the wear and tear of its components, variations in manufacturing processes, and tool snaps. These failures can result in revenues losses, backorders, unplanned maintenance actions and safety hazards such as leakage of toxic materials, machine-tool crashes and permanent damage to components of machine-tools. To avert unexpected machine-tool failures a preventive maintenance policy can be adopted for the manufacturing system. According to the policy guidelines maintenance actions can be executed on a periodic basis or in response to the machine-tool condition. Performing maintenance periodically can be a costly option because maintenance activities are carried out even though machine-tools are in good condition. On the other hand condition-based maintenance (CBM) which is performed on the basis of the condition of machine-tools is likely to cut down cost by trimming unnecessary maintenance operations.

CBM relies heavily on sensors to detect deviations in important physical parameters that determine the health of machine-tool components to indicate potential problems and incipient failures in machine-tools. Recent developments in micro-electromechanical systems (MEMS) and sensor data processing techniques have led to the dawn of smart sensors. In contrast to their counterpart traditional sensors, smart sensors can perform better condition-based monitoring of machine-tool components. Equipped with on-board processors, smart sensors can quickly process raw sensor data and can promptly detect and predict machine-tool failures [1] [2]. This work presents an algorithm to build a condition-based preventive maintenance plan taking into account the machine-tool failure information provided by smart sensors in a flow-line manufacturing system.

LITERATURE REVIEW

The literature is abound with several decades of extensive research on maintenance planning and execution. A multitude of maintenance models that take into account the various factors that influence the planning and execution of maintenances have been developed. In this paper only research related to group maintenance is reviewed. For an introductory and detailed study of the maintenance literature one may refer to review papers by McCall [3], Pierskalla and Voelker [4], Osaki and Nakagawa [5], Sherif and Smith [6], Jardine and Buzacott [7], Valdez-Flores and Feldman [8], Cho and Parlar [9], Jensen [10], Dekker *et al.* [11], Pham and Wang [12], Van Der Duyn Schouten [13], and Wang [14].

Group maintenance literature can be classified into two main categories. In the first category, all components in a subassembly or components that have some kind of precedence relationship with the faulty component(s) are replaced all at once because it is economically infeasible to replace the faulty component(s). In the second category, maintenance on machines that fail stochastically and have identical failure probability distribution is performed simultaneously [14]. None of the existing group maintenance planning techniques consider the condition of machines (obtained by interpreting sensor-based information) while devising the maintenance plans. The present work is the first in the literature (to the best of the authors' knowledge) that takes the information on condition of machines from smart sensors into consideration when devising a group maintenance plan.

DYNAMIC GROUP MAINTENANCE POLICY

Two types of maintenance strategies can be adopted on the basis of failure information provided by smart sensors. In the first strategy (on-the-fly maintenance) machines are repaired independently as and when the sensor-based information becomes available, and in the second strategy (group maintenance) maintenance for a group of machines is performed simultaneously. The frequent shutdowns of the flow-line system for maintenance and high repair costs are the limitations of on-the-fly maintenance strategy. These limitations can be addressed if group maintenance strategy is adopted. In the group maintenance strategy the parallel performance of maintenance actions decreases the number of shutdowns and reduces the maintenance costs to some extent however at the expense of the sacrificing usable machine life [15]. The proposed maintenance algorithm adopts the group maintenance strategy.

Costs involved

The costs that are taken into consideration while preparing the proposed maintenance plan are, repair cost, revenue loss, and cost per hour to sacrifice usable machine life. The repair cost of a machine includes the labor cost, the cost of procuring components that need to be replaced in the machine, and the cost of materials required to perform the repair. The revenue loss for a machine is computed as the product of maintenance duration, theoretical production rate, and the profit earned per job. The cost per hour of sacrificing usable machine life is the ratio of the average repair cost per machine to the mean time between failures of a machine.

In developing the algorithm five assumptions were made: (a) smart sensors do not fail in predicting machine-tool breakdowns, (b) all predictions are certain and correct, (c) all machines have the same

failure rate, (d) machines, after receiving maintenance, are as good as new machines, and (e) there is no upper limit on the maintenance cost.

Dynamic group maintenance algorithm

The objective of the dynamic group maintenance algorithm is to group machines for maintenance such that the cost that can be saved by grouping maintenances increases. Let T_1, T_2, \dots, T_N ($T_{i+1} > T_i, \forall i$) be the times at which maintenance actions are scheduled for M machines that are predicted to fail ($M > 1, M = N$). For the ease of explanation, let time instances $T_1, T_2, \dots, T_i, \dots, T_N$ be referred to as stage 1, 2, ..., i, \dots, N and let G_i represent the set of machines that need to be maintained at stage i .

Step 1: Initialize set G_i with machines that require maintenance at stage i .

Step 2: Start at the penultimate stage, $i = N - 1$.

Step 3: At stage i compute

- $R(i)$, the net savings that result if maintenance action(s) were advanced from stage $i + 1$ to stage i .
- $P(i)$, the cost of sacrificing usable machine life if maintenance action(s) were advanced from stage $i + 1$ to stage i .

Step 4: If $R(i) > P(i)$, then $G_i = G_i \cup G_{i+1}$ and $G_{i+1} = \{\emptyset\}$.

Step 5: Update $i = i - 1$.

Step 6: If $i = 1$ go to Step 2 otherwise terminate the algorithm.

The net savings obtained if maintenance actions were advanced from stage $i + 1$ to stage i is computed as,

$$R(i) = R_p C_{profit} T_s + C_{setup}$$

where, $T_s = \min(a, b)$, $a = \max_{j \in G_i} \{T_{d_j}\}$ and $b = \max_{j \in G_{i+1}} \{T_{d_j}\}$.

In the above expression, R_p is the theoretical production rate, C_{profit} is the profit per piece, T_s is the downtime that is curtailed, C_{setup} is the setup cost to shutdown and restart the flow-line, and T_{d_j} is the repair time of machine j . One setup cost is saved when maintenance of machines at stage $i + 1$ is advanced to stage i . The cost $P(i)$ of sacrificing usable machine life of machines in set G_{i+1} if their maintenances were advanced from stage $i + 1$ to i is computed as,

$$P(i) = \sum p (T_{i+1} - T_i)$$

where p is the cost of sacrificing a unit of usable machine life of a machine.

The clusters or groups of maintenance actions obtained from the algorithm are valid for the machine failure information that is currently available. When new information about machine failure is available, the dynamic group maintenance algorithm is applied taking into account the updated set of machines that need maintenance.

SIMULATION AND RESULTS

Two simulation models were built. Both the models simulate a flow-line manufacturing system integrated with smart sensors. In the first model, dynamic group maintenance policy is adopted whereas in the second model, on-the-fly maintenance policy (no group maintenance) is implemented. The simulation models are built in Java. Table 1 lists the parameters used in both simulation models.

Table 1: Parameters used in the two simulation models

Parameter	Flow-line system employing dynamic group maintenance	Flow-line system employing on-the-fly maintenance
Number of machines	80	Same
Part processing time	1 min	Same
Machine breakdown probability	0.0002	Same
T_d is identical for all machines	10 min	Same
R_p	25 jobs per hour	Same
C_{profit}	\$5	Same
C_{setup}	\$100	Same
p	\$3 per hour	N/A
Repair cost	\$15	Same

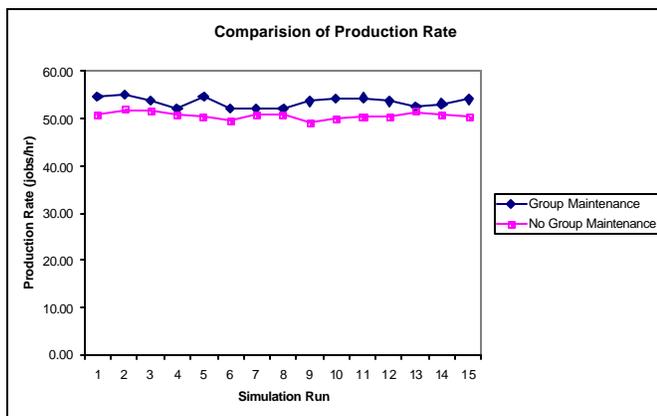


Figure 1: Comparison of production rate

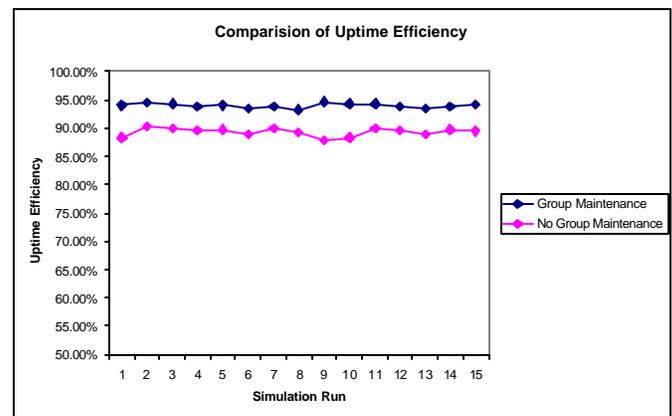


Figure 2: Comparison of uptime efficiency

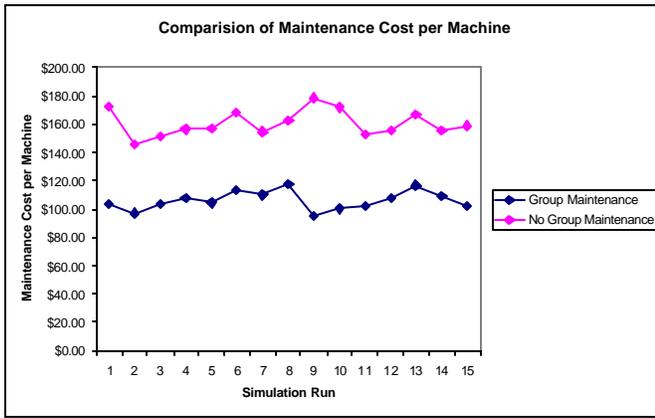


Figure 3: Comparison of maintenance cost

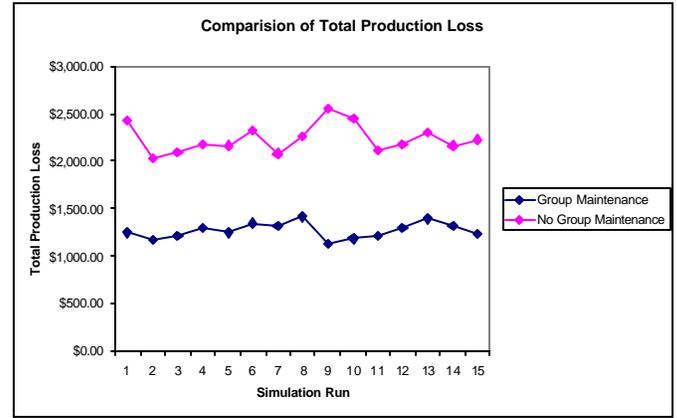


Figure 4: Comparison of production loss

The two scenarios are compared in terms of their production rate, uptime efficiency, maintenance cost per machine, and the total production loss. Figures 1, 2, 3, and 4 illustrate the simulation results. It is evident from these plots that the production rate, uptime efficiency, maintenance cost per machine (consists of setup and repair costs), and net savings are higher when the dynamic group maintenance algorithm is applied. The difference in production rate and uptime efficiency is not blatantly pronounced between the two maintenance policies. Whereas the maintenance cost per machine and the production loss are 51% and 77% higher in case of group maintenance policy, which clearly indicate the advantage provided by maintenance clustering.

CONCLUSIONS

The current work presents a heuristic group maintenance algorithm that takes the machine-tool failure prediction from smart sensors in devising maintenance plans. Adopting a group maintenance policy can reduce the frequency of shutdowns for maintenance which results in an increase in production rate and uptime efficiency, reduction production loss, and a decrease in maintenance costs although at the cost of sacrificing some usable machine life. Sample runs of the simulation model of a flow-line manufacturing system integrated with smart sensors and employing a dynamic group maintenance policy and the same manufacturing system using on-the-fly maintenance strategy indicate the advantages of grouping maintenance activities in terms of production rate, uptime efficiency, maintenance cost, and production loss.

REFERENCES

- [1] P. G. Ranky, "Smart Sensors," *Sensor Review*, vol. 22, pp. 312-318, 2002.
- [2] S. Vadde, S. V. Kamarthi, and S. M. Gupta, "Modeling of Smart Sensor Integrated Manufacturing Systems," 2003, *Proceedings of the SPIE International Conference on Intelligent Manufacturing*, vol. 5263, pp. 30-37.

- [3] J. J. McCall, "Maintenance policies for stochastically failing equipment: A survey", *Management Science*, 1965, Vol. 11, No. 5, pp 493-524.
- [4] W. P. Pierskalla and J. A. Voelker, "A survey of maintenance models: the control and surveillance of deteriorating systems", 1976, *Naval Research Logistics Quarterly*, Vol. 23, pp. 549-554.
- [5] S. Osaki and T. Nakagawa, "Bibliography for reliability and availability of stochastic systems", 1976, *IEEE Transactions on Reliability*, Vol. 25, pp. 285-287.
- [6] Y. S. Sherif, M. L. Smith, "Optimal maintenance models for systems subject to failure – A review", 1981, *Naval Research Logistics Quarterly*, Vol. 28, No. 1, pp. 47-74.
- [7] A. K. S. Jardine and J. A. Buzacott, "Equipment reliability and maintenance", 1985, *European Journal of Operations Research*, Vol. 19, pp. 285-296.
- [8] C. Valdez-Flores and R. M. Feldman, "A survey of preventive maintenance models for stochastically deteriorating single-unit systems", 1989, *Naval Research Logistics*, Vol. 36, pp. 419-446.
- [9] D. I. Cho and M. Parlar, "A survey of maintenance models for multi-unit systems", 1991, *European Journal of Operations Research*, Vol. 51, pp. 1-23.
- [10] U. Jensen, "Stochastic models of reliability and maintenance: An overview", 1995, *Proceedings of the NATO Advanced Study Institute on Current Issues and Challenges in the Reliability and Maintenance of Complex Systems*, pp. 3-36.
- [11] R. Dekker, R. E. Wilderman, and F. A. Van Der Duyn Schouten, "A review of multi-component maintenance models with economic dependence", 1997, *Mathematical Methods of Operational Research*, Vol. 45, No. 3, pp. 411-435.
- [12] H. Pham and H. Wang, "Imperfect maintenance", 1996, *European Journal of Operations Research*, Vol. 94, pp. 425-438.
- [13] F. A. Van Der Duyn Schouten, "Maintenance policies for multicomponent systems", 1995, *Proceedings of the NATO Advanced Study Institute on Current Issues and Challenges in the Reliability and Maintenance of Complex Systems*, pp. 117-136.
- [14] H. Wang, "A survey of maintenance policies of deteriorating systems", 2002, *European Journal of Operations Research*, Vol. 139, pp. 469-489.
- [15] R. E. Wilderman, R. Dekker, and A. C. J. M. Smith, "A dynamic policy for grouping maintenance activities", 1997, *European Journal of Operations Research*, Vol. 99, pp. 530-551.