www.sjm06.com

Serbian Journal of Management 17 (1) (2022) 51 - 60

Serbian Journal of Management

MAINTENANCE POLICY SELECTION OF N-COMPONENT REPAIRABLE SYSTEM USING GENETIC ALGORITHM

Nishit Kumar Srivastava[a]*, Pratyay Kuila[b], Namrata Chatterjee[a], A K Subramani[c] and N Akbar Jan[a]

[a]*ICFAI Business School (IBS), IFHE Deemed to be University, Hyderabad, Pin Code: 501203, India*

[b]*National Institute of Technology Sikkim, Barfung Block, Ravangla, South Sikkim - 737139, India*

[c]*St. Peter's College of Engineering and Technology, Chennai, Pin Code: 600054, India*

(Received 11 Ocrober 2020; accepted 21 January 2022)

Abstract

A typical manufacturing system consists of a large number of repairable components/ machines which age with time and require maintenance. This paper proposes a novel maintenance policy selection method using genetic algorithm. Where, maintenance problem is formulated for n-component repairable system to minimize the total maintenance cost. The various maintenance policies and repairable components are represented in the form of chromosomes, initially various chromosomes are randomly generated which are then assessed and selected using fitness value and then crossover and mutation function is performed to obtain a better chromosome. Several iterations are performed till the desired results is achieved. The proposed algorithm is further explained and validated through an illustrative example.

Keywords: Artificial Intelligence (AI), corrective maintenance, preventive maintenance, predictive maintenance, Genetic Algorithm (GA)

1. INTRODUCTION

Ageing factor in manufacturing systems is inevitable and every machine degrades with time requiring maintenance at regular interval. Maintenance is an activity performed in order to restore a machine or a system back to its acceptable working condition (Ahmad & Kamaruddin, 2012; Hsiao et al., 2013; Aarab et al., 2017; Srivastava et al., 2018). Maintenance is one of the most critical operations performed in

* *Corresponding author: nks.ism@gmail.com*

DOI: 10.5937/sjm17-28807

any manufacturing system and may reach up to fifty percent of the total cost of the product. Maintenance has several benefits such as: reliability improvement of the system, reduced down times, improved component life, reduced equipment failure, reduced energy consumption, better product quality, improved working condition and safety, better asset protection, reduction in spare part inventory, reduction in catastrophic failure, lower insurance cost, productivity improvement, etc. (Neves et al., 2011; You et al., 2011; Costa et al., 2012; da Silva et al., 2012; Guo et al., 2014; Tsarouhas, 2015; Srivastava & Mondal, 2016). However, maintenance poses several challenges as well which needs to be catered like: cost of labor, cost of training, cost of equipment used, rate of depreciation of assets, change of technology, etc (Curcuru et al., 2010; Costa et al., 2012; Hu et al., 2012; Babu et al., 2013; Guo et al., 2014; Darwish et al., 2016; Aarab et al., 2017). Last half century has seen drastic developments in maintenance techniques and methods improving reliability, reducing downtimes and reduced wastages in manufacturing sector. Several types of maintenance policies have been developed in the recent past such as corrective maintenance, breakdown maintenance, preventive maintenance, predictive maintenance, total productive maintenance, condition-based maintenance, artificial intelligence-based techniques, etc. (Bevilacqua & Braglia, 2000; Dhillon, 2002; Moghaddam & Usher, 2011; Ahmad & Kamaruddin, 2012; Hsiao et al., 2013; Joo & Min, 2013; Srivastava & Mondal, 2015; Abbas et al., 2019).

It is highly important to make a judicious selection of a maintenance policy for a particular machine. Bevilacqua and Braglia (2000) proposed AHP based maintenance policy selection model for Italian oil refinery where the authors rank ordered various maintenance policies using seven different performance parameters. Ierace and Cavalieri (2008) used Fuzzy logic and Analytic Hierarchy Process (AHP) separately for maintenance policy selection and compared the results showing differences in results where both the methods adopted excelled in separate parameters and superiority of any single technique could not be established. Azadeh and Zadeh (2015) proposed AHP-fuzzy MCDM approach to establish rank difference in various maintenance policies and select the most appropriate one. Methods used in the above cases are more subjective in nature leading to a result which may not be fully relied upon moreover it is considered that the whole plant is applying the same maintenance policy on each and every component which may not be economical in the chosen case. It is well known that a manufacturing system consists of several machines and based on the machine configurations/sequences, allowed downtimes and maintenance cost application of maintenance techniques may vary. If a system of m number of components is considered with possibility of applying n number of different maintenance policies on each component it becomes increasingly difficult to arrive at the right combination of maintenance policies for various components in the system. This paper presents a novel maintenance policy selection model using genetic algorithm (GA) in order to minimize maintenance cost of manufacturing systems.

2. OVERVIEW OF GENETIC ALGORITHM

Genetic algorithm (GA) falls under the

category of heuristic search algorithms motivated by Charles Darwin's theory of biological evolution (Limmun et al., 2019). Jhon Holland in 1975 developed this algorithm which was later on popularized through the work done by Goldberg in 1989. The evolutionary properties of genetic algorithm have contributed to its success and has emerged as the major contributor to the wide field of computational intelligence (Engelbrecht, 2002). It is more efficient and powerful method compared to random and exhaustive search algorithms (Kinnear, 1994; Limmun et al., 2013; Limmun et al., 2019). Genetic Algorithm is a widely accepted and popular heuristic approach for several optimization problems (McCall, 2005; Kuila et al., 2013; Arjestan, 2017). It begins with generation of various random possible solutions known as initial population. Each solution in the initial population is represented in the form of an array or string of genes known as chromosome or an individual. Each individual or chromosome quality is measured through fitness function. Fitness function is then chosen in such a manner that an individual or chromosome results into a near optimal solution. After generation of the initial population, two chromosomes are randomly selected which act as parent chromosome and is used to produce two children chromosome by crossover process. In crossover, randomly selected parent chromosomes genetic information is exchanged. To get better solution child chromosomes further undergo mutation process to restore their lost genetic codes or values. Typically, mutation process helps in overcoming the trap of local optima and happens with an extremely low probability. After crossover and mutation process is over, fitness function for each child chromosome is evaluated and compared to all previously generated chromosomes. In order to ensure that the current generation betters the old generation, two chromosome of older generation bearing poor fitness value is replaced with youngest generated chromosomes. (Goldberg, 1989; Michalewicz, 1992; Kinnear, 1994; Haupt & Haupt, 2004). Flowchart in Figure 1 depicts the various steps of genetic algorithm.

3. SYSTEM MODEL AND PROBLEM FORMULATION

Let there be *n* maintenance strategies and *m* components/machines in an

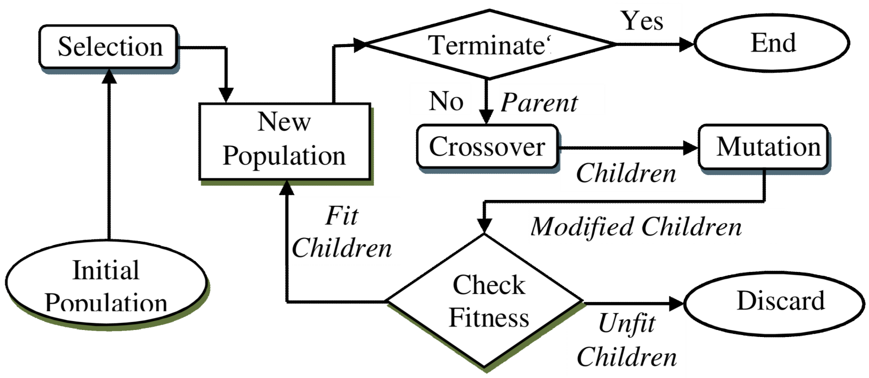

Figure 1. Flowchart of genetic algorithm (Kuila et al. 2013)

industry/system. Now our objective is to select maintenance strategy for each of the components/machines so that the maintenance cost will be minimized. For the better understanding of the above problem we would like to describe first the following terminologies:

1) The set of maintenance strategies is denoted by $P = \{p_1, p_2 ..., p_n\}$.

2) The set of components/machines is denoted by $C = \{c_1, c_2 ..., c_m\}$.

3) M_{ij} denotes the maintenance cost of p_i for c_j. It is assumed that $M_{ij}, \forall i, 1 \le i \le n, \forall j, 1 \le j \le m$ is known.

4) D_{ij} denotes the downtime cost per unit of time of p_i for c_j.

5) t_{ij} be the downtime for p_i in c_j.

6) M_c be the miscellaneous cost.

7) α_{ij} be the Boolean variable such that

$$\alpha_{ij} = \begin{cases} 1, & \text{if } p_i \text{ is applied to } c_j. \\ 0, & \text{Otherwise} \end{cases} \tag{1}$$

The optimization problem of selection of maintenance strategy in form of Integer Linear Programming (ILP) can be written (Formulized) as follows :

$$\text{Minimize} F = \sum_{i=1}^{n} \{ \sum_{j=1}^{m} (M_{ij} + D_{ij} \times t_{ij}) + M_C \} \times \alpha_{ij} \tag{2}$$

Subject to constraints:

$$\sum_{i=1}^{n} \alpha_{ij} = 1, \ \forall j, 1 \le j \le m \qquad (i)$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \alpha_{ij} = m \qquad (ii)$$

The constraint (i) ensures that only a single maintenance strategy can be applied to a particular machine at a time. The constraint (ii) ensures the application of maintenance strategy on all machines.

4. PROPOSED ALGORITHM

In this section chromosome representation methodologies, initial population generation and fitness function determination are discussed followed by chromosome selection process, crossover process and mutation.

4.1. Chromosome representation

Here chromosome represents string of maintenance strategies which indicates the selection of strategy for a particular machine as follows. The chromosome length is same as the number of machines in the manufacturing system. Note that the repetition of same value i for any other gene position j is possible as more than one machine can be maintained by the same strategy. An example chromosome representation is shown in Figure 2.

Example: Consider a manufacturing organization with ten machines and three maintenance strategies i.e., C = $\{c_1, c_2 ...,$

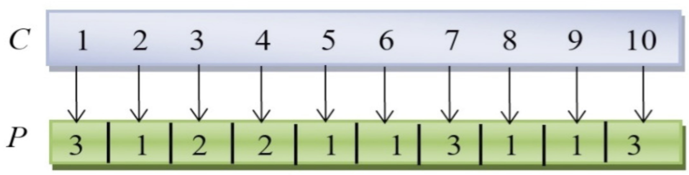

Figure 2. Chromosome representation

c_{10}} and P = {p_1, p, p_3}. Here length of chromosome is ten same as represented in Figure 2. Gene value at position 5 is 1 and it implies that the strategy p_1 is selected for c_5. Similarly, p_1 and p_3 are selected for c_2 and c_7 respectively in this representation.

4.2. Initial Population

Initial population consists of set of chromosomes generated randomly. Each chromosome represents a sequence of maintenance strategies. Chromosomes are generated such that the value say i of the j^{th} position gene is selected randomly such that p_i □P. It is clear that the proposed GA based approach does not have dependency on any particular algorithm for initial population generation. However, it is also evident that all the generated chromosomes in the initial population represent a complete solution.

4.3. Fitness Function

In this step fitness function is developed in order to evaluate each and every chromosome from the initial population. The fitness function is as equation (2), i.e.,

$$F = \sum_{i=1}^{n} \{ \sum_{j=1}^{m} (M_{ij} + D_{ij} \times t_{ij}) + M_C \} \times \alpha_{ij}$$

The main objective is to minimize F.

4.4. Selection

Selection is the process which determines that from the current population which chromosomes will mate (crossover) to create a new set of chromosomes. In the process of chromosome selection some chromosomes having higher fitness value are selected. The individual chromosomes having better fitness value have higher chances of selection. Various selection methods are there that is: roulette wheel selection, tournament selection, rank selection, etc. (McCall, 2005; Wang, 2011; Kuila et al., 2013). Here tournament selection method is used in selecting best fitness value chromosomes from the population. Chromosomes selected in the process are used to produce new offspring's (chromosomes) through crossover operation as shown in proceeding section.

4.5. Crossover and Mutation

Crossover operation is performed on two chromosomes selected randomly from the population. For producing new offspring's of the randomly selected parent chromosome, one point crossover is performed. In this a single point is selected at random and parent chromosome exchange information beyond that point (Afif et al., 2020). Complete process is as shown in figure 3.

The mutation process is applied to the new child chromosome to enhance its quality. Here, a gene position is randomly selected and it is replaced by any other valid value. Generally, the mutation rate become within the range of 1per cent to 5 per cent

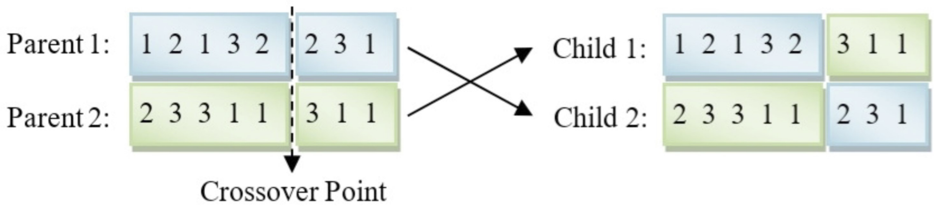

Figure 3. Crossover Operation

(Kuila et al., 2013).

The crossover and the mutation process are repeated until a certain termination criterion or for a predefined number of generations. Finally, the best chromosome of the population is selected as the final solution.

5. ILLUSTRATIVE EXAMPLE

Here, a scenario with five machines and three maintenance strategies is considered with the following data given in Table 1 to Table 5. According to Ming Tan and Raghvan (2008), all maintenance strategies can be broadly categorized under three main headings that is 1) Corrective maintenance, 2) Preventive maintenance and 3) Predictive maintenance, hence only three maintenance strategies have been considered in this example.

Few chromosomes are randomly generated for the initial population as

Table 1. Machine 1 data

Machine 1	Maintenance Strategy		
	Corrective	Preventive	Predictive
Maintenance Cost	900	1000	1050
Downtime cost	500	500	500
Downtime	2 hrs	1.5 hrs	1 hrs
Miscellaneous cost	300	300	300

Table 2. Machine 2 data

Machine 2	Maintenance Strategy		
	Corrective	Preventive	Predictive
Maintenance Cost	900	1100	1100
Downtime cost	470	470	470
Downtime	2.5 hrs	2 hrs	1 hrs
Miscellaneous cost	350	350	350

Table 3. Machine 3 data

Machine 3	Maintenance Strategy		
	Corrective	Preventive	Predictive
Maintenance Cost	1200	1600	1670
Downtime cost	450	450	450
Downtime	2 hrs	1.5 hrs	1 hrs
Miscellaneous cost	200	200	200

Table 4. Machine 4 data

Machine 4	Maintenance Strategy		
	Corrective	Preventive	Predictive
Maintenance Cost	800	700	850
Downtime cost	480	480	480
Downtime	1.5 hrs	1.25 hrs	1 hrs
Miscellaneous cost	250	250	250

Table 5. Machine 5 data

Machine 5	Maintenance Strategy		
	Corrective	**Preventive**	**Predictive**
Maintenance Cost	450	600	800
Downtime cost	250	250	250
Downtime	2 hrs	1.25 hrs	1 hrs
Miscellaneous cost	150	150	150

discussed in section 4.3. Using selection process, certain number of chromosomes with better fitness value are selected as new population. Now, the crossover and mutation operation is repeatedly applied on the new population chromosomes. Let *ParentCh*1={2 1 3 1 2} and *ParentCh*2={3 1 2 2 3} be the two randomly selected chromosomes for crossover operation. Fitness value of *ParentCh*1 can be calculated using equation (2) as:

$$\begin{aligned} F(ParentCh1) = &(1000 + 500\times1.5 + 300) \\ &+ (900 + 470\times2.5 + 350) \\ &+ (1670 + 450\times1.0 + 200) \\ &+ (800 + 480\times1.5 + 250) \\ &+ (600+250\times1.25+150) = 9627.5 \end{aligned}$$

Same way fitness value of *ParentCh*2 can be calculated as F(*ParentCh*2) = 9500. Now, crossover operation on crossover point 3 (Randomly selected point) is applied. Therefore, the two generated child chromosomes are *Child*1={2 1 3 2 3} and *Child*2={3 1 2 1 2}. Although mutation rate is very low, here mutation is applied on any one of the child (say *Child*2). A gene position is randomly selected as mutation point (4th gene position of *Child*2, i.e., 1) and randomly changed as 3, i.e., mutated *Child*2={3 1 2 3 2}. Now, fitness value of *Child*1 and *Child*2 is calculated as F(*Child1*) =9545 and F(*Child2*)=9455.

It can be observed that both the children are better than their parent, as the objective is to minimize the fitness value. Therefore, in the current population *Child*1 replaces *ParentCh*1 and *Child*2 replaces *ParentCh*2. Thus, the new population quality enhances generation by generation. Note that, if the fitness value of the child chromosome is not better than its parent, it will not replace the parent.

6. CONCLUSION

In this paper GA based maintenance policy selection algorithm is proposed. The proposed algorithm is then illustrated with an example where a hypothetical situation is modeled using the proposed algorithm. Results showed that in the iterative process the children gene created from the parent gene bettered the parents and provided better solution. This encouraging finding may further be extended to real world problems leading to further development of proposed algorithm.

Reference

Aarab, S., Barkany, A.E., & Khalfi, A.E. (2017). The integration of maintenance plans and production scheduling taking account of outsourcing: a literature review, International Journal of Productivity and Quality Management, 21 (1), 1–22.

ИЗБОР ПОЛИТИКЕ ОДРЖАВАЊА Н-КОМПОНЕНТНОГ СИСТЕМА КОЈИ СЕ МОЖЕ ПОПРАВИТИ КОРИШЋЕЊЕМ ГЕНЕТСКОГ АЛГОРИТМА

Nishit Kumar Srivastava*, Pratyay Kuila, Namrata Chatterjee, A K Subramani, N Akbar Jan

Извод

Типичан производни систем се састоји од великог броја поправљивих компоненти/машина које временом старе и захтевају одржавање. Овај рад предлаже нову методу избора политике одржавања користећи генетски алгоритам. Проблем одржавања је формулисан за н-компонентни систем који се може поправити да би се минимизирали укупни трошкови одржавања. Различите политике одржавања и компоненте које се могу поправити су представљене у облику хромозома, у почетку се различити хромозоми генеришу насумично, затим се процењују и бирају коришћењем вредности погодности, а затим се врши укрштање и функција мутације да би се добио бољи хромозом. Изводи се неколико итерација док се не постигну жељени резултати. Предложени алгоритам је даље објашњен и потврђен кроз илустративни пример.

Кључне речи: Вештачка интелигенција (ВИ), корективно одржавање, превентивно одржавање, предиктивно одржавање, генетски алгоритам (ГА)

Abbas, N.N., Ahmed, T., Shah, S.H.U., Omar, M., & Woo, H. (2019). Investigating the applications of artificial intelligence in cyber security. Scientometrics, 121 (2), 1189-1211.

Afif, M.H., Ghareb, A.S., Saif, A., Bakar, A.A., & Bazighifan, O. (2020). Genetic algorithm rule-based categorization method for textual data mining. Decision Science Letters, 9 (1),37–50.

Ahmad, R., & Kamaruddin S. (2012). An overview of time-based and condition-based maintenance in industrial application. Computers & Industrial Engineering, 63 (1), 135-149.

Arjestan, M.E. (2017). Efficient optimization of multi-objective redundancy allocation problems in series-parallel systems. Decision Science Letters, 6, 307-322.

Azadeh, A., & Zadeh, S.A. (2015). An integrated analytic hierarchy process and fuzzy multiple- criteria-decision-making simulation approach for maintenance policy selection. Simulation, 92 (1), 3-18.

Babu, A.S., Sanghi, U., Rehman, A.U., Shayea, A.M.A., & Sharaf, M.A.F. (2013). A model to derive software maintenance policy decision. International Journal of Productivity and Quality Management, 11 (3), 247–268.

Bevilacqua M., & Braglia, M. (2000). The analytic hierarchy process applied to maintenance strategy selection. Reliability Engineering and System Safety, 70 (1), 71–83.

Costa, C.A.B., Carnero, M.C., & Oliveira, M.D. (2012). A multi-criteria model for auditing a predictive maintenance programme. European Journal of Operational Research, 217 (2), 381– 393.

Curcuru, G., Galante, G., & Lombardo,

A. (2010). A predictive maintenance policy with imperfect monitoring. Reliability Engineering and System Safety, 95 (9), 989–997.

da Silva, P.R.N., Negrao, M.M.L.C., Vieira, P.J. & Sanz-Bobi, M.A. (2012). A new methodology of fault location for predictive maintenance of transmission lines. Electrical Power and Energy Systems, 42 (1), 568–574.

Darwish, M.A., Alenezi, A.R., & Goyal, S.K. (2016). Determination of maintenance schedule and process mean of production system. International Journal of Productivity and Quality Management, 17 (2), 258–271.

Dhillon, B.S. (2002). Engineering maintenance- A modern approach. CRC Press. Florida.

Engelbrecht, A.P. (2002). Computational Intelligence: An Introduction. John Wiley & Sons Inc., Hoboken, NJ 07030, USA.

Goldberg, D. E. (1989). Genetic Algorithms in Search, Optimization, and Machine Learning. Addison-Wesley Longman Publishing Co., Inc., Boston, MA, United States.

Guo, B., Song, S., Ghalambor, A., & Lin, T.R. (2014) Offshore Pipelines, 2nd ed. Elsevier, Waltham, USA.

Haupt, R.L., & Haupt, S.E. (2004). Practical Genetic Algorithms. John Wiley & Sons, Inc., Hoboken, New Jersey.

Hsiao, Y.L., Drury, C., Wu, C., & Paquet, V. (2013). Predictive models of safety based on audit findings: Part 1: Model development and reliability. Applied Ergonomics, 44 (2), 261-273.

Hu, J., Zhang, L., & Liang, W. (2012). Opportunistic predictive maintenance for complex multi-component systems based on DBN-HAZOP model. Process Safety and Environmental Protection, 90 (5), 376–388.

Ierace, S., & Cavalieri, S. (2008). Maintenance strategy selection: a comparison between fuzzy logic and analytic hierarchy process. 9th IFAC Workshop on Intelligent Manufacturing Systems, Szczecin. Poland. 228-233.

Joo, S.J., & Min, H. (2013). A multiple objective approach to scheduling the preventive maintenance of modular aircraft components. International Journal of Services and Operations Management, 9 (1), 18 – 31.

Kinnear, K.E. (1994). Advances in Genetic Programming. MIT Press. Cambridge, MA 02142, US.

Kuila, P., Gupta, S.K., & Jana. PK. (2013). A novel evolutionary approach for load balanced clustering problem for wireless sensor networks. Swarm and Evolutionary Computation, 12, 48- 56.

Limmun, W., Borkowski, J. J., & Chomtee, B. (2013). Using a Genetic Algorithm to Generate D-optimal Designs for Mixture Experiments. Quality and Reliability Engineering International, 29 (7), 1055- 1068.

Limmun, W., Chomtee, B., & Borkowski, J. (2019). Constructing model robust mixture designs via weighted G-optimality criterion. International Journal of Industrial Engineering Computations, 10 (4), 473–490.

McCall, J. (2005). Genetic algorithms for modelling and optimization. Journal of Computational and Applied Mathematics, 184 (1), 205–222.

Michalewicz, Z. (1992). Genetic Algorithms + Data Structures = Evolution Programs. Springer- Verlag, Berlin.

Ming Tan, C., & Raghvan, N. (2008). A framework to practical predictive maintenance modeling for multi-state systems. Reliability Engineeing and System Safety, 93 (8), 1138-1150.

Moghaddam, K.S., & Usher, J.S. (2011).

Sensitivity analysis and comparison of algorithms in preventive maintenance and replacement scheduling optimization models. Computers & Industrial Engineering, 61 (1), 64-75.

Neves, M.L., Santiago, L.P., & Maia, C.A. (2011). A condition-based maintenance policy and input parameters estimation for deteriorating systems under periodic inspection. Computers & Industrial Engineering, 61 (3), 503–511.

Srivastava, N.K., & Mondal, S. (2015). Predictive maintenance using modified FMECA method. International Journal of Productivity and Quality Management, 16 (3), 267–280.

Srivastava, N.K., & Mondal, S. (2016). Development of predictive maintenance model for N- component repairable system using NHPP models and system availability concept, Global Business Review, 17 (1), 105–115.

Srivastava, N.K., Mondal, S., Chatterjee, N., & Parihar, S. (2018). Identifying critical factors for various maintenance policies: A study on Indian manufacturing sector. International Journal of Productivity and Quality Management, 25 (1), 41-63.

Tsarouhas, P.H. (2015). Evaluation of maintenance management through the overall equipment effectiveness of a yogurt production line in a medium-sized Italian company. International Journal of Productivity and Quality Management, 16 (3), 298–311.

Wang, M., Yu, G., & Yu, D. (2011). Mining typical features for highly cited papers. Scientometrics, 87 (3), 695-706.

You, M.Y., Li, H., & Meng, G. (2011). Control-limit preventive maintenance policies for components subject to imperfect preventive maintenance and variable operational conditions. Reliability Engineering and System Safety, 96 (5), 590–598.