IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE)
e-ISSN: 2278-1684,p-ISSN: 2320-334X, Volume 15, Issue 1 Ver. III (Jan. - Feb. 2018), PP 18-24
www.iosrjournals.org

Intelligent Maintenance System by Using MARKOV Chain with Monte Carlo Simulation Approaches

Dr. Elsayed A Elsayed[1] , Dr.Shaik Dawood.A.K.[2] , Abdul Rahaman[3]
Dr.R. Karthikeyan[4]
[1-3](*College of Engineering, King Khalid University, Abha, KSA*)
[4](*Management studies, Karpagam University, Coimbatore, India*)
Corresponding Author: Dr. Elsayed A Elsayed[1]

Abstract : *This paper presents Markov chain technique as a tool for forecasting the suitable maintenance of machines that helps managers in organizational decision making. Markov process is a tool to predict that it can be make logical and accurate decisions about various aspects of management in the future. Monte Carlo simulation is manipulated in this paper and a new methodology for determination of the transition probabilities in a Markov Decision Process is done. It also illustrates three suggestions for plant maintenance and determines the best plant as a decision support for manager*

Keywords: *Markov Chain, Forecasting, Maintenance, Transition matrix.*

Date of Submission: 20-01-2018 Date of acceptance: 09-02-2018

I. Introduction

1.1 Systematic Maintenance

Since the Industrial Revolution, maintenance of equipment is still a challenging issue because of various factors including complexity, cost, and competition. Each year billions of dollars are spent on engineering equipment maintenance worldwide, and it means there is a definite need for effective asset management and maintenance practices that can positively influence success factors such as quality, safety, price, speed of innovation, reliable delivery, and profitability. A good maintenance program requires company-wide participation and support by everyone ranging from the top executive to the shop floor personnel. A machine's breakdown true cost is sometimes difficult to measure. A recent survey showed that the cost for a machine breakdown is more than just the maintenance labor and materials to make the repair. A recent survey showed the actual cost for a breakdown between four to fifteen times the maintenance costs. When the breakdown causes production to stop, the costs are very high because no parts are being produced.

There are several common forms of maintenance. Maintenance problems are general whether it is machines in a workshop, an oil rig, a dairy, or a road tunnel. Some systems are well thought-out and contribute to operating a tunnel that is safe for all that use it. Other haphazard forms of maintenance, based on uncoordinated activities, do not provide the levels of safety needed. Planned maintenance Tunnel maintenance should be planned maintenance. A planned maintenance system consists of preventive maintenance, which can be periodic or equipment condition based, but will always include an element of corrective/ unexpected maintenance, which it is neither possible nor economically reasonable to try to eliminate. The figure below illustrates the different types of planned maintenance that may be used:

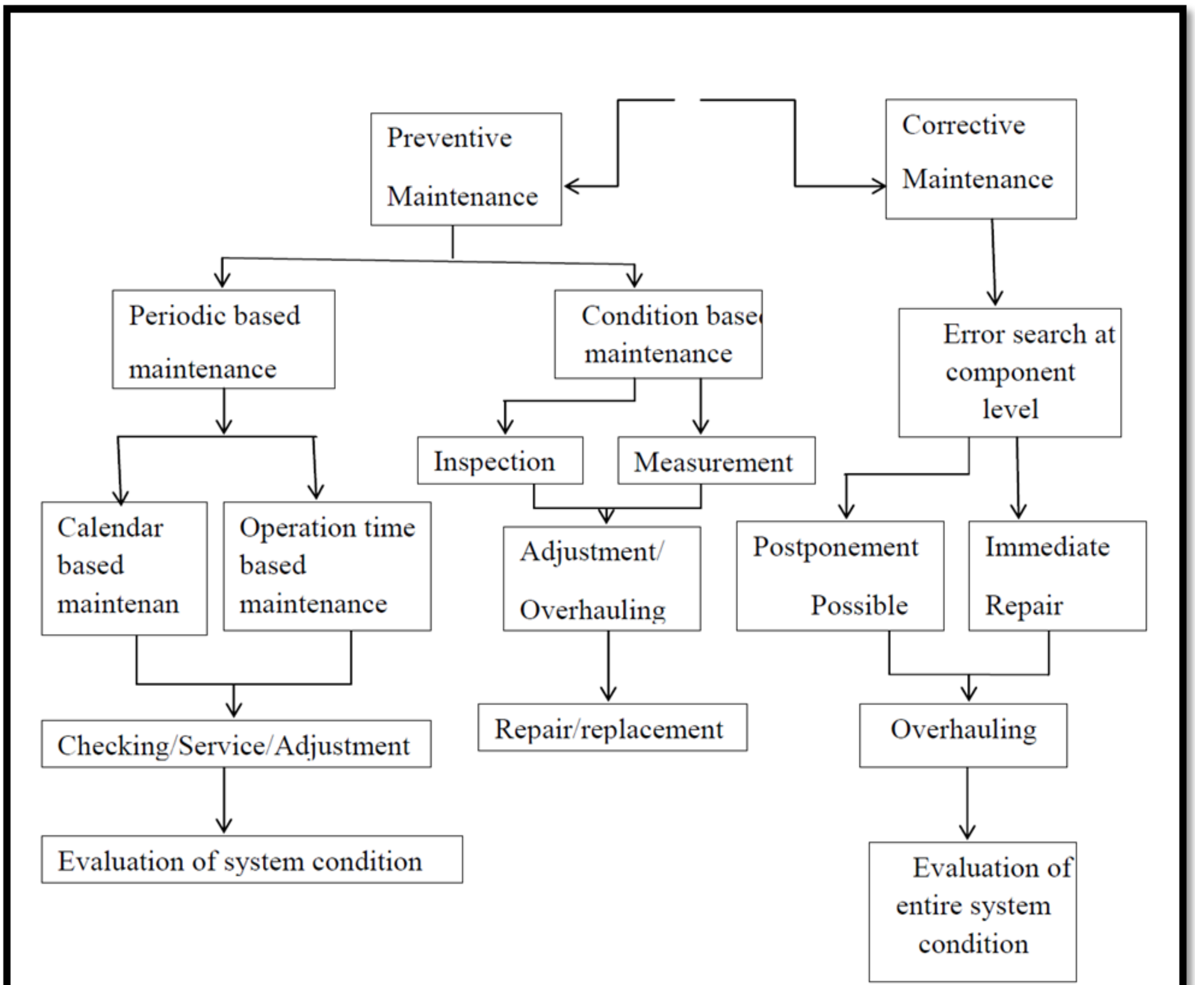

Figure1: Planned Maintenance

Figure1: Planned Maintenance

1.2 Markov Processes

The field of Markov chains has been widely used in management science that these can include:

1. Human resources planning model
2. Pyramid Maslow's model on human needs
3. Model to predict price changes.
4. Changes in brand by customer product
5. Behavior of customer receivables
6. Maintenance models
7. Inventory control
8. Describing a particular type of storage issues
9. Analysis and replacement human resources
10. Prediction of system reliability

II. Literature Review

We will illustrate some of the main researches which manipulates the circumstances of the concepts of our paper. Elmira Popova, et al.[3] illustrates that the cost of maintenance interventions incurred includes the labor (manpower) cost, cost for new parts, or emergency order of expensive items. At the plant management level there is a budgeted amount of money to be spent every year for such operations, and they made statistical analysis is performed on a set of maintenance cost and failure data gathered at the South Texas Project Nuclear Operating Company (STPNOC) in Bay City, Texas, USA.

Andrew K.S. Jardine, et al. [2] attempts to summarize and review the recent research and developments in diagnostics and prognostics of mechanical systems implementing CBM with emphasis on models, algorithms and technologies for data processing and maintenance decision-making. Realising the increasing trend of using multiple sensors in condition monitoring, the authors also discuss different techniques for multiple sensor data fusion. The paper concludes with a brief discussion on current practices and possible future trends of CBM.

Abubaker Shagluf; A. P. Longstaff [1], presents a review of maintenance management methodologies to evaluate the contribution of maintenance strategies, and to find a balance between predictive calibration, on-machine checking and lost production due to inaccuracy. This work redefines the role of maintenance management techniques and develops a framework to support the process of implementing a predictive calibration program as a prime method to supporting the change of philosophy for machine tool calibration decision making.

P. Vrignat, et al.[6], deals with the proposition of using Hidden Markov Models to track and estimate the degradation of a system, according to observations (maintenance activities registered in a database). In a first time, the degradation level of process was established by a "classical" degradation laws (statistical laws). In a second step, this level was established by Hidden Markov Model (probabilistic laws).Tests conducted on the synthesis model, for which degradation levels were known, allowed us to implement the method.

O. A. Adebimpe and et al. [5], identifies some preventive maintenance parameters in manufacturing firms and used to develop cost based functions in terms of machine preventive maintenance. The proposed cost based model considers system's reliability, cost of keeping spare parts inventory and lost earnings in deriving optimal maintenance interval.

Jodie L. Evansetand and et al. [4], reviews the recent research completed on the determination of the probability distribution of the time of breakdown on a freeway. The methodology applied was unique, in that, it applied Markov chains to develop the probability distribution of the time of breakdown. To develop an improved methodology for the prediction of breakdown, the probability distribution of the time of breakdown was determined based on the zonal merging probabilities with respect to the vehicles traveling on the throughway. Freeway flow, available gaps, and drivers' actions as they approach the merge area were taken into consideration in developing the model.

Dr Elsayed A Elsayed, Dr A.K. Shaik Dawood and et al. [7], identifies study helps those who responsible on make the economic plans and the social development in the estimation of the expected numbers of engineers per year and the number of students who will register newly in the college study can be able to give a clear idea about the importance of the statistics and mathematics in the field of strategic planning.

III. Indentations And EQUATIONS

A discrete time Markov chain is a Markov process whose state space is a finite or countable set, and whose time (or stage) index set is T = (0, 1, 2,…). In formal terms, the Markov property is that for all time points n and all states $i_0, \ldots, i_{n-1}, i, j$.

$$P\{X_{n+1} = j | X_0 = i_0, \ldots, X_{n-1} = i_{n-1}, X_n = i\} = P\{X_{n+1} = j | X_n = i\}$$

It is customary to label the state space of the Markov chain by the nonnegative integers {0, 1, 2, …} and to use $X_n = i$ to represent the process being in state i at time (or stage) n.

The probability of X_{n+1} being in state j given that X_n is in state i is called the one-step transition probability and is denoted by $\mathbf{P}_{ij}^{n,n+1}$ That is:

$$P_{ij}^{n,n+1} = P\{X_{n+1} = j | X_n = i\}$$

Since probabilities are non-negative and since the process must make a transition into some state, it follows that:

$$P_{ij} \geq 0 \quad \text{for } i, j = 0,1,2 \ldots$$

$$\sum_{j=0}^{\infty} P_{ij} = 1 \quad \text{for } i = 0,1,2 \ldots$$

A Markov process is complete defined if its transition probability matrix and initial state X_0 (or, more generally, the probability distribution of X_0) are specified.

3.1 Intelligent Maintenance System

Intelligent maintenance systems (IMS) Predict and Forecast equipment performance so "near-zero breakdowns" status is possible. Near-zero downtime focuses on machine performance techniques to minimize failures. Data comes from two sources: sensors (mounted on the machines) and the entire enterprise system (including quality data, past history and trending). By looking at data from these sources (current and historical), it can predict future performance and determine the best plant for future maintenance.

3.2 Data collection:

Data acquisition step (information collecting), to obtain data relevant to system. By using the main common cases of machine, the first-order Markov probability model used in this paper is assumed to have the following characteristics. First, there is a population of individuals that moves among a finite set of *E* different states in a sequence of trials *t* = E1, E2, E3, E4. For a sample of size N from the population there are five years (5×365) day of observation that change over time according to independent and identically distributed time homogeneous Markov chains with *Ei* states. The discrete random variable *Xt* (*Et*= E1, E2, E3, E4) can be used to represent the state of an individual in the population.

Where:

E1: The case that the machine works in excellent condition

E2: There are simple defected but not make the machine stop and its production more than 70% from case 1.

E3: There are major defect and make the production machine less than 70% from case 1.

E4: There is/are main defect/s and machine is stopped.

Data processing step (information handling), to handle and analyze the data or signals collected about the different cases of machine for better understanding and interpretation of the data.

We can represent the system as a discrete time Markov chain with the following state transition probabilities (rows represent present states, columns represent next states):

Table 1: Historical Data for Different Cases of Machine

Case / Day	E1	E2	E3	E4	year
Year1	290	35	25	15	365
Year2	235	45	50	35	365
Year 3	200	55	60	50	365
Year 4	182	62	66	55	365
year5	170	65	75	55	365
Sum	1077	262	276	210	1825
%	0.59	0.14	0.15	0.12	1

3.3 Transition Matrix Pij**:**

A transition matrix, *P* = [*pij*], as a matrix of probabilities showing the likelihood of machine case staying unchanged or moving to any of the other categories over a given time horizon. Each element of the matrix, *pij*, shows the probability of case machine being equal to *i* in period *t*-1 machine case E equal to *j* in period t.

We impose a simple Markov structure on the transition probabilities, and restrict our attention to first-order stationary Markov processes, for simplicity [[1]]. The final state, *R*, which can be used to denote the loss category, can be defined as an absorbing state. This means that once an asset is classified as lost, it can never be reclassified as anything else.

Under this framework, the only relevant information for explaining the behavior of the series is its behavior in the previous period. This assumption of a first-order Markov process for credit transitions may be somewhat restrictive if machine state responds slowly to changes in production working. Markov process or a longer time horizon may be more appropriate. However, using higher order processes or longer horizons increases the complexity and data requirements quite substantially, and may not be feasible with only a limited time series. It may also be the case that machine itself responds quickly to changes in fundamentals, but observations on machine are only made infrequently. Similarly, when using some sources of information on machine such as supervisory data, the observed variable is not true machine case but the supervisor's assessment of the data reported to it. Ideally, one could use hidden Markov chains to model the latent machine case variable, using supervisory observations as the observed (or emitted) model. However, the data requirements of this approach are immense and thus are not practical for the applications considered in this project.

Estimating a transition matrix is a relatively straightforward process by Monte Carlo simulation, if we can observe the sequence of states for each individual unit of observation, i.e., if the individual transitions are observed. For example, if we observe the case of machine at the beginning of a year and then again at the end of its case until the end of the year, then we can estimate the probability of moving from one state to another (E1-E2, E1-E3, E1-E4, E2-E1, ...E4-E4). The probability of a firm having a particular case at the end of the years of observation which make as a sample from life years of machine, (e.g., E1, E2,..,E4) given their case Eij at the beginning of the year is given by the simple ratio of the specific machine that began the year with the same case

(E1) and ended with an E4 case. We can estimate the probability of an individual being in state *j* in period *t* given that they were in state *i* in period *t*-1, denoted by *pij*, using the following formula:

$$P_{ij} = \frac{n_{ij}}{\sum n_{ij}}$$

Thus, the probability of transition from any given state *i* is equal to the proportion of specific machine that started in state *i* and ended in state *j* as a proportion of all time in that started in state *i*.

Using the method of Monte Carlo approach, it is possible to estimate a transition matrix using count data. Anderson and Goodman (1957) show that the estimator given in previous equation is a maximum-likelihood estimator that is consistent but biased, with the bias tending toward zero as the sample size increases. Thus, it is possible to estimate a consistent transition matrix with a large enough sample 1825 day.

Historical data are used to determine the primary transition probabilities. Very often, these data are unavailable, or difficult to get, and in the meantime are subject to various influences and changes in the environment.

The accuracy of the estimates of the transition probabilities determines the accuracy of the Markov model. These estimates are frequently made relying on inadequate or incorrect data. Sometimes they are only based on expert opinion. It is better if they are derived from cohort studies, but again may be imprecise or subject to selection bias. Small samples or short following of the modeled process produce confidence intervals that are large relative to the transition probabilities.

The usual approach is to observe, from historical data, the way in which a system transits from a state to another, for every stage of the process, and use this to derive/estimate the transition probabilities. The other way, is to use experienced engineers to estimate the probabilities using expert opinion. But many other ideas and methods are developed in different fields of Markov processes applications.

By using Monte Carlo simulation, can be estimate the transition matrix by using 1000 random numbers for the cumulative probabilities of the different cases of specific machine.

Table 1: Transition Numbers of Different Cases

	E1	E2	E3	E4	Sum
E1	354	85	89	68	596
E2	91	18	17	12	138
E3	86	23	35	16	160
E4	56	14	18	17	105

Then we can compute the transition probability matrix as in table 2.

Table 2: Transition matrix for machine conditions

	E1	E2	E3	E4	Sum
E1	177/298	85/596	89/596	17/149	1
E2	91/138	3/23	17/138	2/23	1
E3	43/80	23/160	7/32	1/10	1
E4	8/15	2/15	6/35	17/105	1

3.4 Cost Estimation for Maintenance

Operation and maintenance includes all activities necessary for a tunnel to meet all its functional requirements throughout the service life. Different countries have different definitions of maintenance and operation. One universal measurement of maintenance performance, and perhaps the measure that matters most in the end, is the cost of maintenance. Unfortunately maintenance costs are often used to compare maintenance performance between companies or between plants within the same company. Equally unfortunately, there is no standard for measuring maintenance costs. Each company, usually each plant within a company and often each department within a plant develop their own definition of "maintenance costs.". Maintenance cost comparisons should always be accompanied by a clear definition of what is included and excluded for each plant included in the comparison.

The table 3 below shows to what degree the different technical cost elements influence total maintenance costs:

Table 3: The different technical cost elements with influence

Technical equipment system	**Influence**
Incoming power supplies	low
Internal power distribution	low
Standby generation	Standby generation
UPS systems	Moderate
Lighting Ventilation	high
Ventilation	**Low**
Drainage	Moderate
Firefighting	Moderate
Communications	Moderate
Traffic management	low
Traffic monitoring	Low
Building services	Low
Plant monitoring and control equipment	Moderate

The table 4 shows the different technical cost for three different plants estimated by maintenance engineer in the company due to machine under study and all similar machines in the company.

Table 4: Different Estimated Cost

Case	Cost $	Maintenance Specification
E1	0	Idle condition
E2	2000	Simple maintenance
E3	8000	high maintenance
E4	18000	very high maintenance

Table 5: Maintenance Costs with different Plant

	E1	E2	E3	E4
Plan 1	Idle	H.M(8000SR)	V.H.M(18000SR)	V.H.M(18000SR)
Plan 2	Idle	Simple M(2000SR)	H.M(8000SR)	V.H.M(18000)
Plan 3	Idle	Idle (0)	V.H.M(18000SR)	V.H.M(18000SR)

If a Markov chain has a stationary distribution, this satisfies:
Yi= YiP
pi = 1 pi ≥ 0 for all i.
Assuming that in the long-run the system reaches equilibrium $[Y_1, Y_2, Y_3, Y_4]$ where
$[Y_1, Y_2, Y_3, Y_4] = [Y_1, Y_2, Y_3, Y_4]P$, and $Y_1 + Y_2 + Y_3 + Y_4 = 1$

Table 6: Maintenance Costs for Steady State with Different Plant

Cases	Steady State Probabilities			
	E1	E2	E3	E4
Case 1	298/419	85/838	89/838	34/419
Case 2	643/940	104/927	69/595	18/205
Case 3	298/419	85/838	89/838	34/419
Plan	Total cost	Cost Details		
Cost Plan 1	4183.77SR	8000(85/838)+18000(89/838)+18000(34/419)		
Cost Plan 2	2732.53SR	2000(104/927)+8000(69/595)+18000(18/205)		
Cost Plan 3	3372.32SR	18000(89/838)+18000(34/419)		

The least cost is the second plan, and then it must be taken in the consideration of the top management, Maintenance decision-making step (decision-making), to recommend efficient maintenance policies.
The last step of a program is maintenance decision-making. Sufficient and efficient decision support would be crucial to maintenance personnel's decisions on taking maintenance actions.

IV. Results

Due to the three cost estimation the plant 2 is the lower cost on the average 2732.53SR, then the manager of the company can adapting this plant to dealing the suitable maintenance for the specific machine which be studied and the similar machine of it.

V. Conclusion

We believe that the following paper directions are required for the next generation of diagnostic and prognostic systems. It is a supplement for fast and precise prognostic approaches, development of the model incorporating more categories of maintenance actions, and establishment of efficient validation approaches. Markov Chains Application and analysis helps in predicting a future state with a matrix of transition probabilities in a precedent state, which helps in locating states of transition system from period to another. Performing preventive maintenance is almost always the best long-term strategy to maintain equipment scheduling. This paper focused on the use of Markov models for deterioration modeling and maintenance optimization, the implementation of the MDP model with the proposed methodology for calculation of the transition probabilities resulted in optimal policy that showed significant improvement in the area of quality maintenance.
The main conclusions of this paper are as follows:

- The majority of the models reviewed in this paper review that models have actually been applied in the industrial maintenance.
- The models discussed in this paper contain a framework which could be successfully applied to the maintenance industry, provided significant adaptation was carried out, which would involve ensuring that factors such as access restrictions due to costs issues are considered.
- One of the constraints to widespread Markov models application in the offshore maintenance industry could be their complexity. Other researchers in the maintenance optimization field have stated that practitioners are unlikely to apply over-complicated models.

References

[1]. Abubaker Shagluf; A. P. Longstaff ; S. Fletcher, "Maintenance Strategies to Reduce Downtime Due to Machine Positional Errors", Centre for Precision Technologies, University of Huddersfield Huddersfield, United Kingdom, 2014.

[2]. Andrew K.S. Jardine, et al. "A review on machinery diagnostics and prognostics implementing condition-based maintenance", Mechanical Systems and Signal Processing 20 1483–1510, (2006).

[3]. Elmira Popova, et., "Basic factors to forecast maintenance cost and failure processes for nuclear power plants", accepted 20 April 2006, Nuclear Engineering and Design 1641–1647, Elsevier B.V., 2006.

[4]. Jodie L. Evans, et. all., "Probability of breakdown at freeway merges using Markov chains", Transportation Research Part B 35, 237:254, College of Engineering, The Pennsylvania State University, USA, 1999.

[5]. O. A. Adebimpe and et.al., "Preventive Maintenance Interval Prediction: a Spare Parts Inventory Cost and Lost Earning Based Model" Engineering, Technology & Applied Science Research Vol. 5, No. 3, 811-817, 2015.

[6]. P. Vrignat, M. Avila, F. Duculty & B. Robles, "Decision support with a markovian approach for maintenance context activities", *ENSI, PRISME* Laboratory, MCDS Team, Bourges, France, HAL Id: hal-00626533, 26 Sep 2011.

[7]. Dr Elsayed A Elsayed , Dr A.K. Shaik Dawood , Dr R. Karthikeyan, " Estimate Survival Time of Students at College of Engineering by Using Makovian Matrix", International Journal of Research in Management Sciences Volume 5, Issue 1, 2017.

Dr. Elsayed A Elsayed "Intelligent Maintenance System by Using MARKOV Chain with Monte Carlo Simulation Approaches." IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE), vol. 15, no. 1, 2018, pp. 18-24.