

Optimum Reliability-Centered Maintenance Task Frequencies for Power System Equipments

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Abstract— This paper describes an approach to optimization of intervals between activities suggested by Reliability-Centered Maintenance (RCM) for power system equipments. Following a brief resume of RCM, it develops a probabilistic model used to optimize the frequency of maintenance tasks. The model is able to simulate many traditional maintenance policies, such as Age Replacement Policy (ARP), Block Replacement Policy (BRP) and Minimal Repair Policy (MRP). Each RCM task type and failure mode can be simulated by a customization of the model. Using a set of quality and productivity indexes typically used to evaluate power systems, a standard optimization model is built, whose analytical solution yields the best maintenance frequency for all RCM activities. An Appendix lists all symbols not defined on the paper.

Index Terms—RCM, Reliability-Centered Maintenance, Maintenance Optimization, Power System, Modeling.

I. INTRODUCTION

RELIABILITY CENTERED MAINTENANCE (RCM) has achieved the status of preferred maintenance practice not only among aviation companies, but also on nuclear and electric industries. Although based on a well structured qualitative methodology, RCM lacks a unified approach to choose the frequency of maintenance activities. This state has forced practitioners to use empirical models or the blind adoption of manufacturer recommendations. Due to the stochastic nature of most failure modes, a method based on their inherent statistical behavior would be best suited to calculate the optimum frequency of maintenance tasks.

This paper describes a methodology for statistical optimization of task frequencies recommended by RCM. Based on maintainability and reliability parameters usually available on historical maintenance databases of electrical utilities, the method pursues the minimization of impacts of maintenance events on enterprise results.

Besides this **Introduction**, the paper has four more sections. The second section, titled **Reliability-Centered Maintenance**, will resume the RCM principles, and its qualitative methods usually adopted to choose maintenance activities. This will be followed by a proposed statistical model, on the third section, **Modeling**, suited to simulate the stochastic behavior of any type of failure mode, including preventive and corrective tasks, and their impacts on enterprise results. This section will also show how the model can be parameterized based on historical data, to each type of RCM activity, to simulate the availability and

performance of any item, in transient and steady states. Finally, on the fourth section, **Optimization**, a strategic set of productivity and quality indexes will be defined and correlated with traditional performance indicators of power systems, using the model. Each index can be used as an objective function in a standard nonlinear optimization problem, as a decision support on maintenance planning. The section will suggest a standard spreadsheet that automates the estimation of optimum maintenance frequency of all RCM activities, similar to the standard forms traditionally used by RCM practitioners. On the **Conclusion** section, tests conducted on the model by Companhia Hidro Elétrica do São Francisco (CHESF), the largest electric utility company from Brazil, will be reported, with some proposed extensions.

II. RELIABILITY-CENTERED MAINTENANCE

Reliability-Centered Maintenance is a structured method to identify maintenance needs of physical and industrial processes [6,7,10]. Born from aeronautical companies, and supported by military industry in USA, RCM has been adopted by nuclear and electric industries, being applied in almost any modern industrial sector, nowadays. Besides recommending preventive activities, RCM also defines a consistent model relating each activity with its subjacent failure mode. The approach involves answering a structured set of questions that identify the following treats of each item:

- **Main functions** – what the user expects;
- **Functional failures** – losses of utility;
- **Failure modes** – failure causing events;
- **Failure effects** – failure dependent events;
- **Failure consequences** – resultant impacts.

Based on failure consequences (on environment, security, economy or process operation), the method suggests, through a structured logic, the most applicable and effective task to combat each failure mode, among the following options:

- **Time-Directed (TD)** – correct before failure;
- **Condition-Directed (CD)** – detect potential failures;
- **Failure-Finding (FF)** – uncover hidden failures;
- **Run-To-Failure (RTF)** – repair after failure.

Following RCM logic, the above order reflects a decreasing knowledge about the failure mechanism. The last task is recommended when the previous ones are not cost

effective, and there is no security or environment issue; otherwise, a project change is mandatory.

III. MODELING

An RCM model must represent its dominant concepts of potential and functional failures. The first, as the detectable event of the start of a functional degradation, also known as a defect; the second as the inability of the item to supply its required function. These states can be better viewed in a graph (Fig. 1) relating the item resistance to failure with its operating cycle, where three conditions are identified:

- **Normal** – before a potential failure;
- **Defect** – between a potential and functional failure;
- **Failure** – after a functional failure.

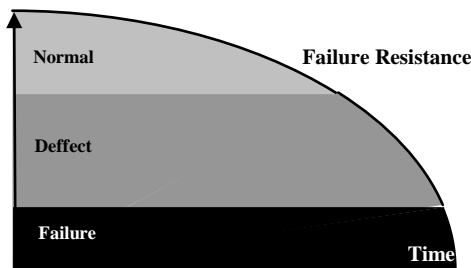


Fig. 1. Failure Resistance Curve

Besides these conditions, the item can be found on a state of preventive or corrective maintenance, according to RCM classification. Following this line, we can define five most probable states of an item, at any time:

- **Normal** – apt to play its function;
- **Preventive** – under preventive maintenance;
- **Failure** – unavailable, after a functional failure;
- **Defect** - available, but with a potential failure;
- **Corrective** – under maintenance, due to potential failure.

We can list, a priori, the following events that change the item state:

- **Preventive**: programmed inspection or maintenance;
- **Corrective**: programmed to correct potential failure;
- **Repair**: forced to correct functional failure;
- **Defect**: partial or potential functional degradation;
- **Failure**: forced functional interruption.

The term “**Corrective**” refers to a planned event (and state) aiming to correct a known potential failure, before its evolution to a functional failure. It differs from a planned “**Preventive**” event (and state) when it is not known if there is a potential failure. The first three events are external maintenance events, while the last two are internal failure events. These events trigger the transitions between the

model states, as shown on Fig. 2.

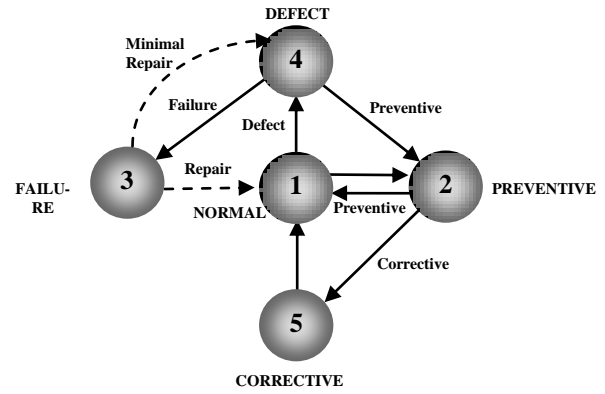


Fig. 2. State Model

The above model can represent the following traditional maintenance policies [9], by a suitable choice between the dotted lines:

- **ARP** – Age Replacement Policy;
- **BRP** – Block Replacement Policy; and
- **MRP** – Minimal Repair Policy.

In an ARP policy, maintenance is done according to operating age of the item, to renew its function (good as new), by an overhaul or substitution before a failure. A BRP policy is a variant of ARP, where each maintenance is done at fixed time intervals. Although easy to manage, it can result on substitution or restoration of items still good to operate. Finally, in an MRP policy, minimal repairs are done, after failures, sufficient to restore the function to a level just before the failure (bad as old), with preventive periodic overhauls or substitution, like ARP and BRP. Table I resumes the meaning of each state, for each standard RCM activity.

Once we have a model, we can use Chapman-Kolmogorov [2,8] equations to quantify each state probability, with the numbering shown on Fig. 2:

$$dP_i/dt = \sum_j (P_j \lambda_{ji}) - P_i \sum_j \lambda_{ij}, \quad i = 1, 2, \dots, 5, \quad (1)$$

where P_i = probability of state i ; and λ_{ij} = rate transition between states i and j .

To be usable, the model must be supplied with its parameters, that is, the failure and defect rates. The method used depends on the kind of RCM activity. For Condition-Directed tasks, the parameter will be determined by the detecting limits (for potential failures) used on inspections, and by their functional failure rates.

TABLE I
CORRELATION AMONG STATES AND RCM ACTIVITIES

STATE→ ACTIVITY↓	NORMAL	PREVENTIVE	REPAIR	DEFECT	CORRECTIVE
Condition Directed	Apt to play its function	Measuring of a functional parameter	Correction of defect after failure	Degradation exceeds potential failure level	Restoration of potential failure
Time Directed	Apt to play its function	Retrofit before end of usable life	Correction after failure at end of usable life	Degradation exceeds overhaul level	Excluded
Failure Finding	Apt to play its function	Functional inspection to find hidden failure	Correction after hidden failure and second event	Functional failure of a hidden function	Hidden failure correction after inspection
Run-To Failure	Apt to play its function	Excluded	Correction after random failure	Excluded	Excluded

For Failure-Finding tasks we need the failure rates of hidden functions, and of events that start multiple failures. For Time-Directed tasks, the parameters will result from acceptable limits of degradation, as determined by the item failure rates, and by consumption rate of process material and lubrication. These can be resumed on two generalized parameters that define the failure behavior of equipments:

- **Defect Rate** – probabilistic density of defects or potential failure in interval dt , conditioned to absence of defect at time t ;
- **Failure Rate** – probabilistic density of functional failure in interval dt , conditioned to absence of failure at time t and presence of defect or potential failure at time 0.

Identification of these parameters in each population of items is a complex endeavor, in modern industrial systems, due to the progressive or hidden characteristic of most defects, with no evidence of the exact instant of occurrence. In consequence, failure rates ($\lambda_f=\lambda_{43}$), and defect rates ($\lambda_d=\lambda_{14}$), key parameters of the process, must be inferred from other observable variables, using the model. These variables are visible events and their duration, such as:

- Forced outage frequency ($F_f=F_{43}$);
- Preventive maintenance frequency (F_p);
- Corrective maintenance frequency ($F_c=1/T_{42}$);
- Mean time to maintain ($MTTM=T_2$);
- Mean time to repair ($MTTR=T_3$); and
- Mean time do correct ($MTTC=T_5$).

Given a population of specimens, these parameters result from a pondered contribution of each item, according to its quantity in the system, as given from statistics and sampled means from the population. The final values may be estimated by measuring the observable history data of each item, in a time window where the maintenance policy and frequency was held constant, sufficient to solve equation 1 in steady state. This will give the failure rate ($\lambda_f=\lambda_{43}$) and defect rate ($\lambda_d=\lambda_{14}$), for each failure mode, for the ARP and BRP (good as new) maintenance policies:

$$\lambda_f = \frac{F_f F_p}{F_c} = \frac{1}{MTTF}, \quad (2)$$

$$\lambda_d = \frac{F_p(F_c + F_f)}{F_p - F_p^2 T_p - F_p F_f T_r - F_c - F_p F_c T_c} = \frac{1}{MTTD} \quad (3)$$

For the MRP (bad as old) policy, the last equation will be:

$$\lambda_d = \frac{F_p F_c}{F_p - F_p^2 T_p - F_p F_f T_r - F_c - F_p F_c T_c} = \frac{1}{MTTD}. \quad (4)$$

These are characteristic parameters of each equipment and operational environment, for each failure mode. The mean time to defect ($MTTD$) is the expected period of operation, without preventive maintenance, before gradual contamination by a latent defect, which may result in a forced outage. The mean time to failure ($MTTF$), defines the expected interval between the contamination and its evolution to an outage; it is like an incubation period, before evolution to a failure.

IV. OPTIMIZATION

Maintenance optimization is achieved by determining values of task periodicity (T_{2l}) and other parameters, such as Mean Times to Maintain ($MTTM$ & $MTTC$) and Repair ($MTTR$), which maximize or minimize an objective function. Some variables must also obey some restrictions, such as physical viabilities, available resources and security requirements. As $MTTM$, $MTTC$ and $MTTR$ are limited by available technology, and assuming they are already at minimum values, the optimization must be sought by adjusting the maintenance frequency. The objective function must reflect the desired result, such as economy, risk, or quality of service.

The performance of a stochastic process may be estimated by a scalar indicator that expresses the cost/benefit of state transition in the system. Each transition can be pondered by a return coefficient (K_{ij}) that measure the gain/loss in the process for each maintenance event. That is:

$$I = K_p F_p + K_r F_r + K_c F_c \quad (5)$$

where I = scalar indicator or objective function;

K_p = preventive return rate;

K_c = corrective return rate;

K_r = repair return rate;

F_p = preventive maintenance frequency;

F_c = corrective maintenance frequency;

F_r = repair frequency.

This is a general expression that can be applied to many indicators in industry [6]. Among them, the following are listed as examples, from power system practice, with the return rates from Table II, and parameters described in the Appendix.

- **EFO** Equipment forced outage;
- **EFD** Equipment forced duration;
- **LPF** Loss of production duration;
- **LPP** Loss of production probability;
- **DNS** Demand not supplied;
- **PNS** Production not supplied;
- **EOF** Equivalent outage frequency;
- **EOD** Equivalent outage duration;
- **PDI** Production discontinuity index;
- **EVC** Enterprise variable cost;
- **CVC** Client variable cost.

Each cell in the table represents the contribution of the population to the indicator, for each type of transition related to a maintenance activity. More detailed definitions of these indexes can be found on reference [6].

TABLE II
RETURN COEFFICIENTS

I	Preventive (K_p)	Repair (K_r)	Corrective (K_c)
EFO	$I + K_a$	$I + K_a$	$I + K_a$
EFD	$K_a T_a + K_r T_p$	$K_a T_a + K_r T_e$	$K_a T_a + K_r T_c$
LPF	$K_{pr} + K_a K_e$	$K_e + K_a K_e$	$K_{pr} + K_a K_e$
LPP	$K_{pr} T_p + K_a K_e T_a$	$K_e T_e + K_a K_e T_e$	$K_{pr} T_c + K_a K_e T_a$
DNS	$W_p + K_a W_a$	$W_e + K_a W_a$	$W_c + K_a W_a$
PNS	$(W_p + K_a W_a) T$	$(W_e + K_a W_a) T$	$(W_c + K_a W_a) T$
EOF	$(Q_p + K_a Q_a) / Q_s$	$(Q_e + K_a Q_a) / Q_s$	$(Q_c + K_a Q_a) / Q_s$
EOD	$(W_p + K_a W_a) T / Q_s$	$(W_e + K_a W_a) T / Q_s$	$(W_c + K_a W_a) T / Q_s$
PDI	$(W_p + K_a W_a) / Q_s$	$(W_e + K_a W_a) / Q_s$	$(W_c + K_a W_a) / Q_s$
EVC	$C_i + K_a C_a$	$C_e + K_a C_a$	$C_c + K_a C_a$
CVC	$C_{is} + K_a C_{as}$	$C_{es} + K_a C_{as}$	$C_{cs} + K_a C_{as}$

The ideal maintenance frequency that optimizes any of these indicators, taken as an objective function I , can be determined by expanding F_p , F_c and F_r on expression (5), from the model equations, in steady state. This allows us to build the following canonical non-linear programming system, for ARP and BRP policies:

Minimize the objective function

$$I = AF_p + \frac{D(B - F_p)}{C + F_p} + \frac{E(B - F_p)F_p}{C + F_p} \quad (6)$$

Subject to the restriction

$$\frac{1}{MTTM} \geq F_p \geq 0 \quad (7)$$

Where A , B , C , D and E are positive parameters:

$$A = K_p \quad (8)$$

$$B = \frac{1}{MTTM} \quad (9)$$

$$C = \frac{\lambda_d + MTTR \cdot \lambda_d \lambda_f + \lambda_f}{1 + \lambda_d MTTT} \quad (10)$$

$$D = \frac{K_r MTTM \lambda_d \lambda_f}{1 + \lambda_d MTTT} \quad (11)$$

$$E = \frac{K_c MTTM \cdot \lambda_d}{1 + \lambda_d MTTT} \quad (12)$$

For the MRP (bad as old) policy, replace parameter C by:

$$C = \frac{\lambda_d + MTTR \cdot \lambda_d \lambda_f}{1 + \lambda_d MTTT} \quad (13)$$

In these expressions, λ_d and λ_f are functions inherent to technology used and production environment. Values of $MTTM$, $MTTC$ and $MTTR$ depend on available maintenance technologies. The unique controllable parameter is the maintenance frequency. It can be null, if Run-To-Failure is the chosen RCM maintenance task, or greater than zero, in case of Condition-Directed, Failure-Finding or Time-Directed RCM tasks. The inferior and superior limits for F_p ($(1/MTTM) \leq F_p \leq 0$) are related to physical viability, as the maintenance frequency can not be negative or greater than the inverse of the mean time do it. Figure 3 shows a typical plot for these expressions, as a function of maintenance frequency.

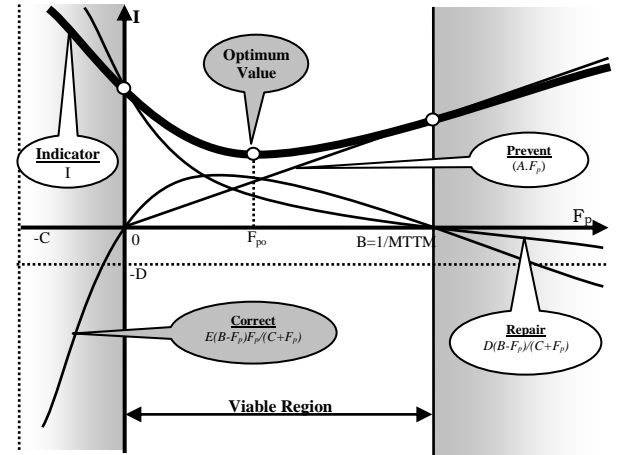


Fig. 3. Quality Indicators

Note that the positive region of indicator I is formed by three parcels. The first, $(A \cdot F_p)$, grows with the increase of preventive maintenance frequency, as a cost onus over the desired objective. The second parcel, $[D(B - F_p)/(C + F_p)]$, decreases with maintenance frequency, as a benefit brought by corrective maintenance. The third parcel, $[E(B - F_p)F_p/(C + F_p)]$, ponder the effects of repair tasks on the indicator. This mix is typical of optimization problems, conducting to an equilibrium point among the parcels. The figure also shows how the three controlled parameters ($MTTR$, $MTTM$ and F_p) affect the result. The greater the $MTTR$, the greater will be the value of D , and the frequency that minimizes the indicator. The same can be said of $MTTM$

and B .

According to classical methods to solve these systems, the optimum maintenance frequency will be given by a non-negative real root of the differential equation:

$$\frac{dI}{dF_p} = 0. \quad (14)$$

By substitution, this equation reduces to a quadratic form, with two real roots [1,2,3]. Solving it gives the optimum maintenance frequency, for the policies ARP, BRP and MRP:

$$F_{po} = \left[C^2 - \frac{AC^2 - D(B+C) + EBC}{A-E} \right]^{\frac{1}{2}} - C. \quad (15)$$

It can be shown that the other root of eq. (14) must be neglected, as it will be negative, contradicting restriction (6). Note that, depending on parameters A , B , C , D and E , both roots will be negative. In this case, the maintenance frequency that optimizes the objective function will be zero, at the border of the viability region. That is, only a Run-To-Failure strategy is recommended, as any preventive maintenance will degrade the objective function.

If, in addition to availability, there is interest in minimizing other indicators such as those from Table II, a much more complex, multi-criteria decision problem (MCDM), will have to be solved. The same model will still be valid for each indicator, and a compromise solution will have to be negotiated among the availability of the equipment, and the other system results.

As is usual with RCM activities, all results must be documented, for each failure mode and maintenance task. According to expression (15), the optimum frequency will be a function of the following data, for each failure mode and task:

Maintainability

- Mean time to maintain ($MTTM$)
- Mean time to repair ($MTTR$)
- Mean time to correct ($MTTC$)

Reliability

- Defect rate (λ_d)
- Failure rate (λ_f)

Productivity

- Return rate to maintain (K_p)
- Return rate do repair (K_r)
- Return rate to correct (K_c)

Periodicity


- Actual maintenance frequency (F_p)

Excluding the last item, all other are difficult data to obtain, considering the lack of reliable statistical information about operating systems. For new systems, good engineering

estimation and judgment must be used to get initial data. Bayesian methods can be used to refine these estimations as experience is gained with the system. Accelerated life tests may be an option for small and inexpensive components. Once used for the first time, successive application of the model will improve the original estimation and results.

The model can be formatted following the standard forms used by RCM, as shown on Fig. 4, or translated into a simple spreadsheet to automate the calculus.

Optimization of Maintenance Frequency

	Unit	Code	Facilitator	Date	Sheet
	Item	Code	Auditor	Date	From

Reference			Task			Maintainability			Productivity			Reliability		Periodicity	
FU	FA	MO	Maintain	Repair	Correct	Maintain	Repair	Correct	Defect	Failure	Actual	Optimum			

Fig. 4. RCM Form for Optimization

V. CONCLUSION

This paper has shown a statistical model of equipment defects and failures, and an approach to optimization of maintenance frequency based on Reliability-Centered Maintenance. Its application to an extensible electrical transmission network, with more then 80 high voltage installations operated by CHESF, has tested its validity. The test was followed by seminars and workshops where managers and specialists have analyzed the results and simulations, as a support tool to decision making. Statistics were determined from maintenance and operation records, covering 9 years. During this period, maintenance policy was held constant, assuring the steady state of equation (1). The models were parameterized to represent several partitions of the system, covering the protection of 1248 high voltage equipments. After optimization of the maintenance tasks of protection items, maintenance and operation records were compared to previous years, assuring optimum results for all quality indexes. Of special interest, all functional tests involving tripping of breakers from protection were cancelled since then, as the model recommended a negative frequency for this task! Other maintenance activities, such as relay checking, were optimized, resulting in annual gains superior to US\$ 500,000.00/year [2].

Due to the general nature of the model, any kind of equipment and industrial activity can be modeled. Its availability opens new ways to add gains to maintenance. By regional modeling, for instance, besides environment influences, one can avail local crew productivity by their mean times to correct, repair and maintain, and network deficiencies by losses of load and generation. Comparison among different families of equipment can be simulated by

modeling their corresponding population, and referencing to benchmarks of the industrial sector. The uniform structure of the model, being independent from equipment type or failure mode, eases the interchange of experiences among companies, and adoption of uniform policies by industrial sectors.

APPENDIX

This appendix lists all symbols and data used on Table II, not defined on the text. Ideally, they should be sampled, for each population of items, and normalized to the same time period. Otherwise, they can be estimated by specialists. Topological data may be generated by contingency analysis, by simulation of the transmission network, to determine the interrupted generation or load during forced and programmed outages of each power system item, in steady state.

C_a	mean utility cost of an accidental outage;
C_{as}	mean client or social cost of an accidental outage;
C_c	mean cost of a corrective maintenance;
C_{cs}	mean client/social cost of a corrective maintenance;
C_e	mean cost of a forced outage;
C_{es}	mean client or social cost of a forced outage;
C_t	mean cost of a preventive maintenance;
C_{ts}	mean client/social cost of a preventive maintenance;
F_e	forced outage frequency;
K_a	accidental rate of maintenance;
K_e	fraction of items that cut load during a forced outage;
K_{pr}	fraction of items that cut load during a maintenance;
K_t	outage fraction maintenance time;
Q_a	interrupted load during an accidental outage;
Q_e	interrupted load during a forced outage;
Q_p	interrupted load during a preventive maintenance;
Q_c	interrupted load during a corrective maintenance;
Q_s	mean or nominal power flow through each item;
T	observation or sample period;
T_a	mean time of an accidental outage;
T_e	mean time of a forced outage;
T_p	mean time of a preventive maintenance outage;
T_c	mean time of a corrective maintenance outage;
W_a	interrupted energy during an accidental outage;
W_e	interrupted energy during a forced outage;
W_p	interrupted energy during a preventive outage;
W_c	interrupted energy during a corrective outage.

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