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THE COMPUTERIZED APPROACH TO OPTIMAL MAINTENANCE POLICY FOR AGING SYSTEMS

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1. Summary and Conclusion

The paper considers renewable (or replaceable) units, assemblies, and similar equipment items with increasing failure rate whose gradual aging is due to depletion of some physical property or material. These items can be periodically inspected and, if necessary, restored. The best maintenance strategy for such items should be based on the Preventive Condition-Directed concept. Several applications of Reliability Centered Maintenance policies were constructed. To investigate them a sophisticated Monte-Carlo model of a system consisting of several aging units was developed. Simulation approved that developed Maintenance policy enables to decrease total repair and downtime cost per unit time not less than 10% in comparison with the repair-at-failure and periodic repair policies.

To implement the elaborated maintenance policies, it is necessary regularly predict an item's remaining lifetime utilizing the information on the current technical state and operating time of an item. This data can be obtained due to non-destructive diagnostics (i.e. inspection). Assuming future operating and environmental conditions to be known or not to change significantly, we construct an adequate aging model and derive a new conditional distribution of remaining life-time.

The developed software package (for IBM PC/AT compatible computer) enables to predict Expected Residual Life-time, Optimal Time Interval to the next inspection, Total Expected Maintenance and Downtime Cost, and other important characteristics using the conditional failure probability function. Its thorough verification versus actual inspection results showed acceptable level of prediction accuracy and consistency (e.g. a relative expected error does not exceed 14%).

2. Basic Definitions, Assumptions and Notations

We consider a unit or assembly capable of performing a specific function which normally operates as a part of a long-term using equipment or as a single-unit system. Item's failure rate increases steadily.

The main assumptions.

1) Aging (or physical degradation) is the primary reason for item's failures.
2) An Item is repairable or replaceable as a whole in case of critical failure.
3) Item's current operating state can be identified by a critical performance parameter (or vector) $A(t)$.
4) Regular inspections allow to ascertain critical performance parameter value a_c at any operating time t_c.
5) The aging status, when a critical performance parameter exceeds the predefined control limit A_{lim} is interpreted as its critical failure. A term "critical" is used as we consider failures causing item's overhaul or replacement.
6) A predefined control limit of a critical performance parameter will also be referred to as a "critical" one.

Examples of actual objects are as follows: an internal-combustion engine with the "Gap between a piston and cylinder" as a critical performance parameter; a mechanical gear with "Thickness of pinion's teeth"; an electrical motor with "Gap in the bearings"; a tire with "Depth of tire's tread", etc.

Let us introduce the following notations:

1) C_{pr}, C_{f1} are cost of preventive and failure repair, respectively;
2) $Q[x \mid a(t_c)=a_c]$ is a conditional failure probability, i.e. a probability of a failure given a critical parameter value is equal to a_c at the operating time t_c.

3. Cost-Effective RCM Policies

The following applications of the Preventive Condition-Directed Maintenance (PCDM), which minimize total expected maintenance and downtime cost per unit time, can be defined. The principal advantage of these policies is a possibility to reschedule any item's renewal in accordance with its actual technical state identified by an actual current value of its critical parameter and operating time. The other beneficial point is a simplicity of their implementation.

a) If an item under consideration can be inspected and/or repaired at any (or almost any) scheduled time, then it is worth estimating optimal residual lifetime of this item x_{opt}. To fulfil this we should calculate total expected cost per unit operating time as a function of remaining lifetime x. The required optimal residual lifetime is such argument value, which minimizes the following expression:

(1)
$$G(x)=[C_{pr}+(C_{ff}-C_{pr})Q[x \mid a(t_c)=a_c]] \,/\, \{t_c+x-\int_0^x Q[t \mid a(t_c)=a_c]\,dt\}$$

The developed cost-effective PCDM policy is presented in Figure 1.

We should take into account possible deviations and errors, including methodic, measurement, diagnostic, and other ones. Therefore, it is recommended to use interval estimations rather than point ones. The graphs of the functional $G(x)$ with possible deviations for two example sets of source data are shown in Figure 2.

b) If the item under consideration can be preventively restored (repaired or replaced) only during inspection downtime, and if the Maintenance Schedule has been already specified for the entire system along with certain inspection interval t_{ins}, we may estimate efficiency of immediate preventive repair (replace) in comparison with operating until next inspection. In other words, cost per unit operating time for immediate preventive repair C_{pr}/t_c should be compared with total expected cost per unit operating time by the end of the next inspection interval, which may be calculated using functional (1), where an inspection interval t_{ins} should be substituted in place of the remaining lifetime x.

The decision available here is obvious:

- if $C_{pr}/t_c < G(t_{ins})$, then immediate preventive repair is cost effective;
- if $C_{pr}/t_c > G(t_{ins})$, then this item is recommended to operate until the next inspection.

c) If an item under consideration is concerned with safety or its reliability has been allocated, we are enabled to predict safe residual lifetime of this item with the aim to provide the required survival probability P. To obtain this result we should solve the following obvious equation: $Q[x \mid a(t_c)=a_c] = 1-P$

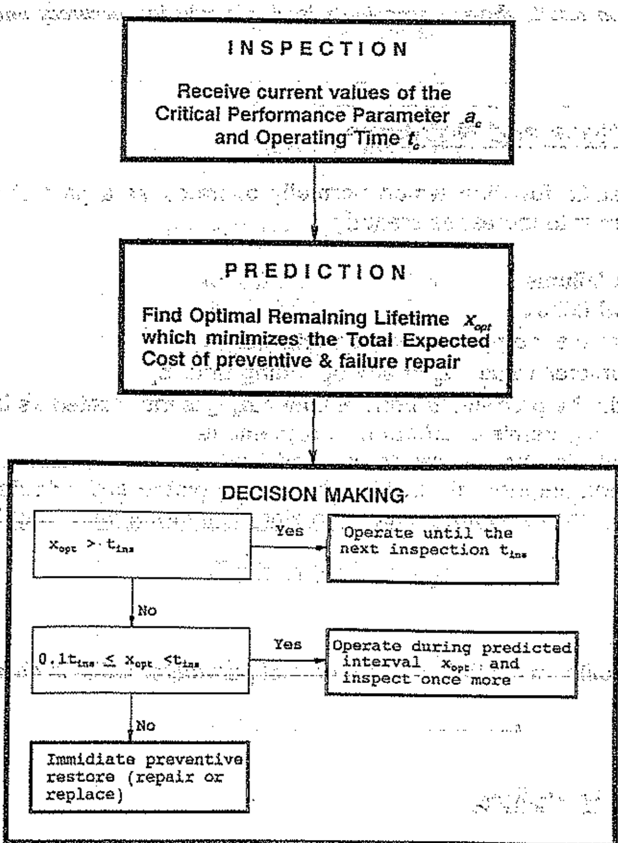

FIGURE 1. THE FLOW DIAGRAM OF THE DEVELOPED COST-EFFECTIVE PCDM POLICY

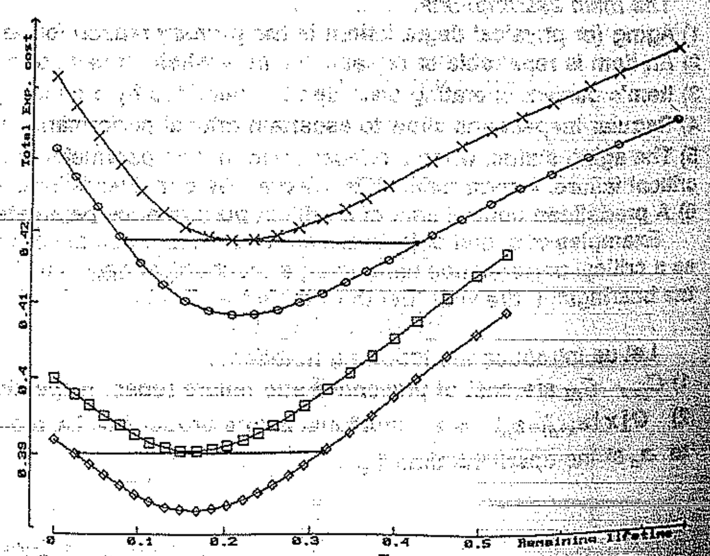

FIGURE 2. TOTAL EXPECTED COST PER UNIT TIME WITH DEVIATION DUE TO SOURCE DATA AMBIGUITY AS A FUNCTION OF REMAINING LIFETIME (EXAMPLES FOR 2 SETS OF INPUT DATA).

"All Prediction Results", or only optimal Remaining lifetime (i.e. "Next Interchanging Point"), or effectiveness of item operating until the next scheduled inspection.

Once calculation is completed, a user may receive several reports. The program provides both table and graph types. Figure 5 presents an example of the table with General prediction results, and Figures 2,6 shows three graph kinds available.

To investigate and verify developed PCDM policy, a complex Monte-Carlo Simulation Model was created. It permits to simulate various stochastic degradation processes along with majority existing classes of maintenance strategies, that is:

- repair-at-failure (i.e. only corrective maintenance);
- restoring in accordance with preliminary schedule;
- variants of PCDM and RCM policies.

The estimated total repair and downtime cost per unit time for the described PCDM strategy was 9 to 12% less than the same criteria for the repair-at-failure and periodic repair policies.

A)

```
DEFINE DATA            CALCULATION                RESULTS

              COST & MISCELLANEOUS  CONSTANT  DATA

               COST  DATA  ASSOCIATE  with  TIRES, $

  Cost  of NEW  tire: 300.00   Cost  of  RETREADED  tire: 200.00
  Cost  of  tire's  mounting-dismounting: 15.00
  Cost  of  tire's PHST procedures: 100.00
  Cost  of vehicle's  downtime losses: 80.00

      INSPECTION  INTERVAL  duration: 10000   km

       STANDARD   DIMENSION  ASSOCIATE  with  TREAD

  Normal depth of NEW tread, mm: 25.0
  Critical limit depth of WORN tread , mm: 5.00

            TIRE's   POSITION  on  axle                 Front
  Left or Right: Right          Front  or Rear  :       Rear

Use //<PgUp>/<PgDn> to move/scroll, <ENTER> to select, <ESC> to abort
 Choose a tire's position: FRONT  or  REAR
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B)

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DEFINE DATA            CALCULATION                RESULTS

              INSPECTION & OPERATION CONDITION DATA
Previous inspections data: DISTANCE run, km    Tread DEPTH, mm
                                   10000              20.0
                                   20000              16.0
                                   30000              14.0

  Current TOTAL RUN, km : 40000

  Current tread DEPTH, mm  : 12.5

  PAVEMENT type : Asphalt, concrete        TERRAIN type : Plain

  TRAFFIC type: City&towns                                Normal (dry)
  Degree of LOADING: MAX     Degree of GRIP with road:    Wet
                                                          Slippery
  Ambient TEMPERATURE: Warm                               Varied

Use //<PgUp>/<PgDn> to move/scroll, <ENTER> to select, <ESC> to abort
Choose a degree of GRIP with pavement
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FIGURE 3. INPUT WINDOWS FOR CONSTANT (A) AND CURRENT INSPECTION (B) DATA.

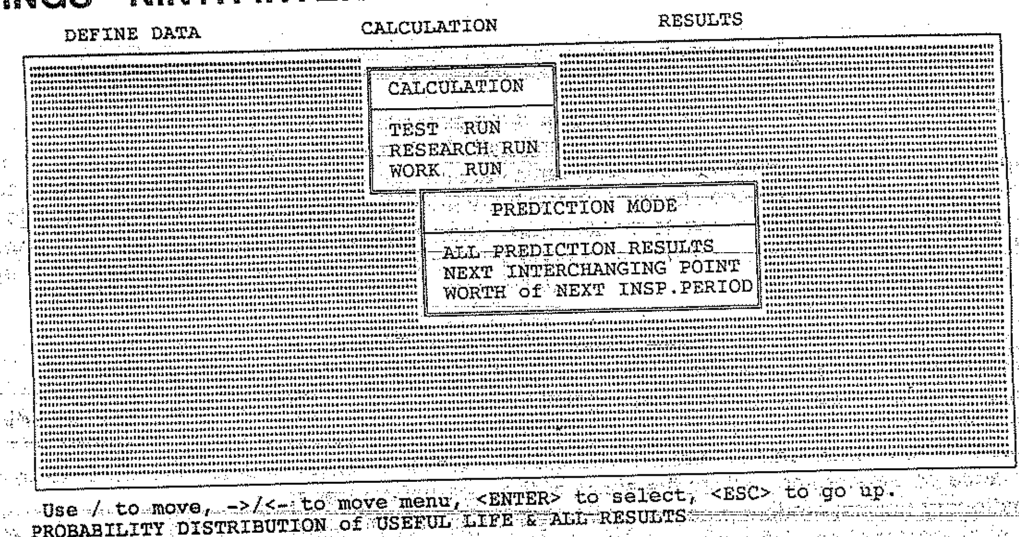

FIGURE 4. THE MAIN SCREEN WITH THE TOP MENU-BAR AND NESTED PULL-DOWN MENUS

	TOTAL RUN, km (-Life duration)	Probability of SUCCESS
Expected (mean) useful life	57700	0.45
Recommended next inspection point (from÷to)	49720 ÷ 50800	0.71
Predicted tire interchanging point	53200	0.68

RECOMMENDED ACTION (variants): 1. Interchanging
2. Retreading
3. Replacing

FIGURE 5. THE TABLE WITH THE GENERAL PREDICTION RESULTS (EXAMPLE)

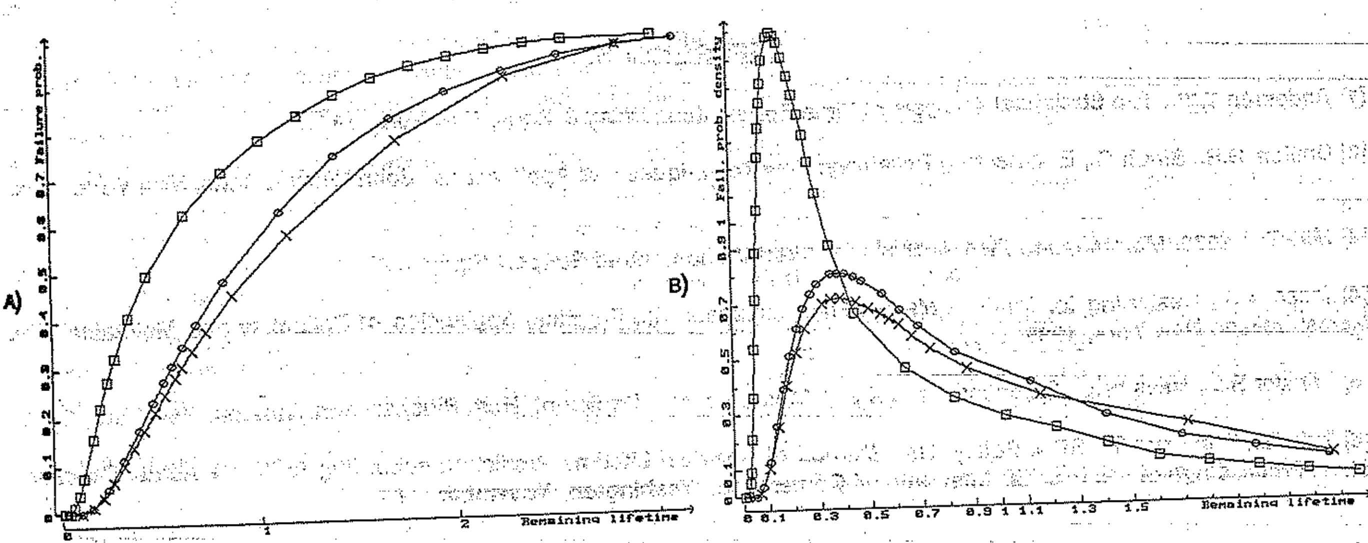

FIGURE 6. CONDITIONAL FAILURE PROBABILITY (A) AND DENSITY (B) AS A FUNCTION OF REMAINING LIFETIME (EXAMPLES FOR 3 DATA SETS).

5. Appendix: Brief Mathematical Foundation

To construct the required model of monotone aging, a large sample of about 15 sets of actual wear-out data (such critical performance parameters as gap between a piston and cylinder in a diesel engine, thickness of pinion's teeth, depth of tire's tread, gap in bearings, etc.) was collected. Stochastic data set for each random process consists of some 10 to 16 time-series measured with definite inspection interval. Preliminary investigation of scatter diagrams for this data indicated, that any process of such type appears to have fairly high correlation between its successive cross-sections [1]. Finally, a stochastic model of monotone change of a critical performance parameter which provides the best fit to actual degradation data is identified by the model:

(3) $$A(t) = \beta + V_k \cdot s(t,\Omega) + \epsilon(t),$$

where β is a parameter's nominal value depending on actual measurement base;
V_k is a random index of parameter speed change, which is considered to be constant for any particular item over the observed operating interval;
Ω is a vector of constants, which indicates inherent mechanism of physical deterioration for each critical performance parameter and defines the sharp of the parameter's trend;
$\epsilon(t)$ is a stationary normal random process, which defines actual data deviations from the trend of each realization.

The main statistical characteristics of the process $\epsilon(t)$ are approved to be as follows:
- an expectation function is obviously equal to zero;
- a standard deviation may be considered as constant σ_ϵ (for each particular performance parameter), as its time dependence is stochastically insignificant.
- an autocorrelation interval τ_{cor} also can be treated as a constant for each performance parameter, so that an autocorrelation process function may be approximated as with the linear) function, that is:

(4) $$\rho_\epsilon(\tau) = \begin{cases} 1-\tau/\tau_{cor}, & \text{if } \tau = t_2 - t_1 < \tau_{cor} \\ 0, & \text{elsewhere} \end{cases}$$

The vector Ω should be estimated utilizing the entire data sample on definite critical performance parameter with the help of the standard Least Square Method (LSM). If we know not less than 4 values of critical parameter for a particular item, the speed index also can be estimated accurately enough according to LSM.

In order to infer conditional failure distribution, we'll use the process model (3) and specify the condition as the following expression for a section of the normal random process $\epsilon(t)$ at the known operating time (refer to [6] for more details): $\epsilon(t_c) = a_c - V_k t_c^\alpha$. To construct the required conditional probability function, we'll write the following correct transformation:

(5) $$P[t_c + x < T \mid \epsilon(t_c) = a_c - V_k t_c^\alpha] = P[a(t_c + x) > 1 \mid \epsilon(t_c) = a_c - V_k t_c^\alpha] =$$
$$= P[\epsilon(t_c + x) > 1 - V_k \cdot (t_c + x)^\alpha \mid \epsilon(t_c) = a_c - V_k t_c^\alpha].$$

Here we may apply the known formulas for the conditional probability of two correlated and normally distributed random variables $\epsilon(t_c)$ and $\epsilon(t_c + x)$, we can easily infer a distribution of the conditional failure probability (2) taking into account necessity of truncation of the normal law with the aim to keep non-decreasing property of the stochastic aging process.

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