

DETERMINING THE OPTIMAL PERIOD FOR RENEWAL
 WITHIN EVOLUTIONARY STRATEGIES

Nicolae Mărășescu

Dunărea de Jos University of Galați

Abstract: This paper deals with the determination of the optimal period for renewal of the equipment described by a reliability model with constant parameters. For this purpose use is made of an evolutionary strategy based on a Markov reliability model. Markov model parameters are adjusted using an ADALINE-type neural network, a trained network using a sliding window.

Key words: Reliability, Markov models, diagnosis, neural networks.

1. Introduction

In order to reduce operation costs of equipment it is necessary that preventive interventions, performed to eliminate accumulated depreciation and maintain performance at levels as close to the nominal ones as possible, be carried out exactly the right time. The correct determination of the optimal preventive renewal period keeps the equipment performance within admissible limits and maximizes its availability. Any premature or delayed action will increase the costs of the equipment operation. Determining the optimal period for renewal can be done using the Markov reliability model of the equipment. For this model to better reflect the current state of the equipment with positive wear, which works in variant external conditions, its parameters have to be adjusted periodically, an action that can be performed using a neural network. Figure 1 shows the structure of the evolutionary renewal system [4].

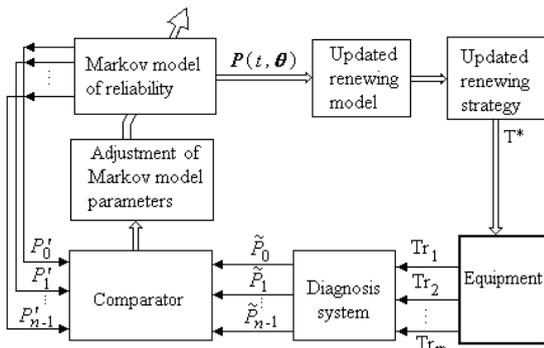


Fig.1. Structure of the evolutionary renewal system

When adjusting the Markov reliability model parameters associated with the equipment use is made of the information provided by a diagnosis system and the probabilities of the states provided by the Markov model. After each adjustment of the

parameters the updated renewal model is determined the optimal time of renewal [5].

Adjusting the parameters of a second-order Markov model associated with the graph in Figure 2 can be done using the following relations:

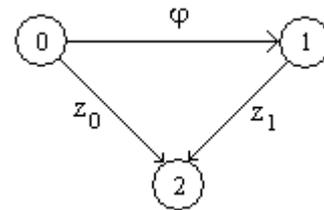


Fig. 2. Graph of 2nd order Markov model

$$P_0[k] = a_0 P_0[k-1] \quad (1)$$

$$P_1[k] = a_1 P_1[k-1] + b_1 P_0[k-1]$$

where:

$$a_0 = \exp[-\Delta t \cdot (z_0 + \varphi_1 + \varphi_3)]$$

$$a_1 = \exp[-\Delta t \cdot (z_1 + \varphi_2)] \quad (2)$$

$$b_1 = \varphi_1 / (z_1 + \varphi_2) \cdot (1 - a_1)$$

The structure used for the adjustment is an ADALINE neural network composed of elements that are trained independently of each other and receive delayed input responses from the diagnosis system. The neural network is presented in Figure 3, where A_1, A_2 are simple elements of type ADALINE. For the discrete time k , the input vectors of these elements are:

$$v_1[k] = \tilde{P}_0[k-1]$$

$$v_2[k] = (\tilde{P}_0[k-1], \tilde{P}_1[k-1])^T \quad (3)$$

where $\tilde{P}_0[k], \tilde{P}_1[k]$ are given by the real-time diagnosis system (Figure 1).

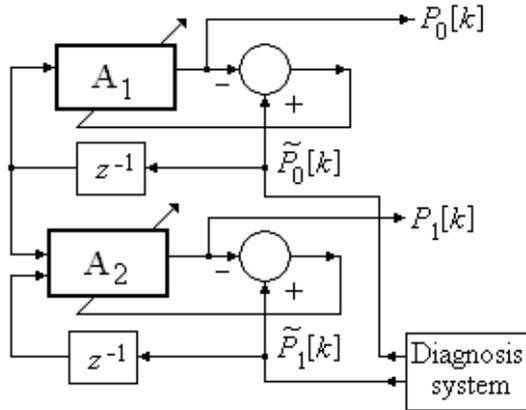


Fig. 3. The structure of the neural adjustment system

The difficulties of adjustment do not depend on the order of the Markov model but on the nature of the input data (constants, variables, linear or nonlinear etc).

2. Calculation of the optimal period for renewal

The optimum time of renewal can be obtained by minimizing the average cost of the equipment maintenance per time unit. The expression of the average cost is given by relation (4) where b is the cost of renewal expressed as a fraction of the cost of restoration carried out in case of failure and H is the renewal function determined according to Markov model.

$$C(T) = \frac{H(T) + b}{T} \quad (4)$$

The minimum function value $C(T)$ is obtained for the optimum period T^* resulting as the solution of equation (5), where h is the density of the renewal.

$$T \cdot h(T) - H(T) = b \quad (5)$$

The real parameters of Markov model (z_0, z_1, φ) determine the value T_0^* of the optimal renewal time. It is assumed that these parameters are not known and, therefore, use is made of their estimates, z_{0est}, z_{1est} and φ_{est} . The values of these estimates are adjusted automatically according to the operating algorithm of the evolutionary renewal system. The synthesis algorithm of the evolutionary strategy renewal system performs recursively the following operations:

- Automatic adjustment of the Markov model parameters using a neural network containing two elements of type ADALINE;

- Calculation of probabilities of good working states, $P_0^k(t)$ and $P_1^k(t)$, at the current step k of the algorithm. Until the current time, t_c , probabilities $P_0^k(t)$ and $P_1^k(t)$ are considered equal to $\tilde{P}_0(t)$ and $\tilde{P}_1(t)$, provided by the diagnosis system and for $t > t_c$ these probabilities are provided by the Markov reliability model. Thus, after each adjustment of the parameters of Markov model, this is used as a predictor of the reliability properties, for $t > t_c$.
- Calculation of the functions $R^k(t), f^k(t), h^k(t)$ and $H^k(t)$, using the values $P_0^k(t)$ and $P_1^k(t)$ obtained in the previous step;
- Determining the optimal period for renewal, $T_{est}^*(k)$ related to the current Markov model and to the remaining time until the next renewal.

To validate the proposed strategy, the actual value of the optimum time for renewal, T_0^* is previously calculated representing the "target" to which must tend the values $T_{est}^*(t)$ obtained at each iteration of the evolutionary renewal algorithm. Considering the initial value $z_0 = 0.005, z_1 = 0.025, \varphi = 0.04$ and $b = 0.1$, for the optimum renewal time the value $T_0^* = 22h$ was obtained. Since at time t_0 the diagnosis system can not provide equipment state information, the Markov model parameters are initialized to values estimated a priori, based on information about that equipment. Two situations will be analyzed:

- initialization values of the estimated parameters are higher than those of the real parameters;
- initialization values of the estimated parameters are lower than those of the real parameters.

Case a: The initialization values of the estimated parameters are: $z_{0est}(0)=0.01, z_{1est}(0)=0.05, \varphi(0)=0.07$. With these values, the calculation of the renewal period leads to $T_0^*(0) = 10h$. If the classical strategy of renewal were used, the important difference between values T_0^* and $T_0^*(0)$ shows that a premature renewal operation would take place, with significant negative effects in terms of cost.

First it was adopted a training window length, q_{max} , equal to 5, the sampling step Δt , being equal to 1. In

this case, until the moment $t=5$, i.e. until the completion of the first training window, the system does not make any adjustment to the Markov model parameters, they remaining at the initialization values. By the time $t=5$ the optimal renewal time is admitted, based on the initialization parameter values, and the data set for training the neural network is completed. Once the first window is completed training of the ADALINE elements is taking place, which results in the estimated values of the Markov model parameters.

On this basis, functions $R^k(t)$, $f^k(t)$, $h^k(t)$, $H^k(t)$, ($k=5$) are determined for the estimated model and then the $T_{est}^*(5)$ value for the optimal period of renewal. The value obtained $T_{est}^*(5) = 28h$ is higher than the real time of renewal $T_0^* = 22h$. The evolution of the optimal renewal period estimated $T_{est}^*(t)$ is shown in Figure 4 (by the *). The same figure illustrates the value of the optimal renewal period for the fixed parameters model (solid line) and the remaining time until the next preventive renewal time (by sign o).

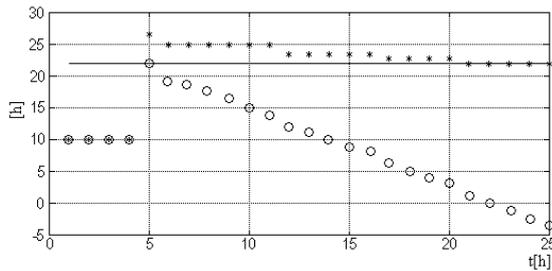


Fig. 4. Evolution of the optimal renewal period in case a, $q=5$

Figure 5 presents the evolution of the values for the optimal period of renewal for a length equal to 1 of the ADALINE elements instruction window, the symbols used having the same meaning as in Figure 4.

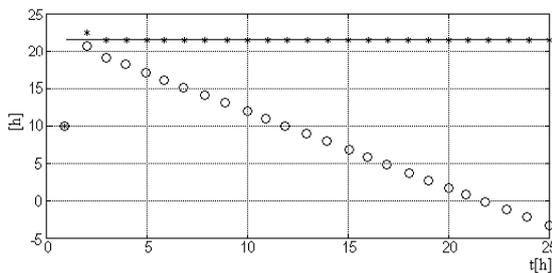


Fig. 5. Evolution of the optimal renewal period in case a, $q=1$

In the event that the length of the training/instruction window is equal to 10, the

results of the optimal renewal period are shown in Figure 6.

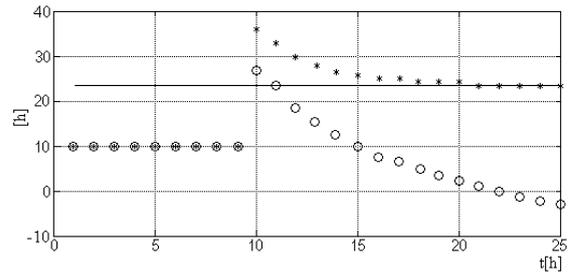


Fig.6. Evolution of the optimal renewal period in case a, $q=10$

The analysis of the results for different values of the neural network training window length, it is found to be advantageous a small length training window so that the first adjustment of the Markov model parameters to be achieved as soon as possible.

Case b: In this case, the Markov model parameters have the same values as described above, and the initialization values of the parameters estimated are: $z_{0est}(0)=0.001$, $z_{1est}(0)=0.02$, $\varphi(0)=0.02$. For these initialization values, the renewal time estimate is $T_{est}^*(0) = 33h$ with respect to the actual value $T_0^* = 22h$. If they use were made of the classical strategy of renewal, it could result in a damage, i.e. a recovery, instead of renewal. Figure 7 presents the optimal renewal time until the next renewal for a training window length value equal to 1. It is noted that the estimates $T_{est}^*(t)$ rapidly converge to the actual value $T_0^* = 22h$, so that the time of the next renewal can be known long before its occurrence.

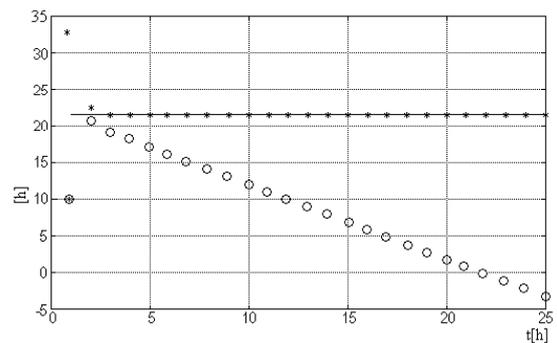


Fig. 7. Evolution of the optimal renewal period in case b, $q=1$

Increasing the length of the instruction window to 5, it is obtained an evolution of the estimated optimal renewal time as in Figure 8.

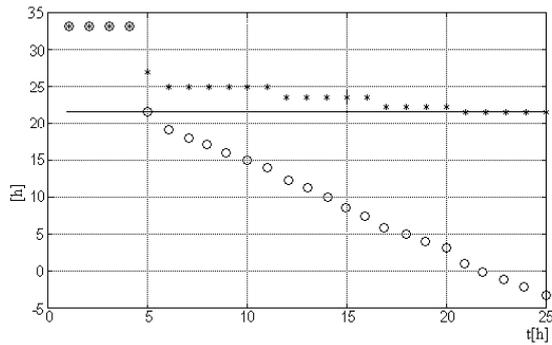


Fig. 8. Evolution of the optimal renewal period in case $b, q=5$

3. Conclusions

Looking at the results obtained it is found that using an evolutionary renewal strategy is a good way to determine the optimum preventive renewals moments. The adjustment strategy based on Markov reliability model using neural network is working accurately even when the initialisation values are quite far from the actual ones, yield convergence of the values of T_{est}^* to the actual value T_0^* . For the adjustable Markov model to better reflect the current reliability properties of the equipment, it is necessary for the training window to have a minimized length.

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