Optimal Preventive Maintenance Strategy Using Reinforcement Learning

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Abstract

Taking optimal maintenance decisions is a challenging process as different maintenance actions have different effects on the system. Maintenance is defined as a set of associated techniques, tools and management actions that aim to maintain or restore the functioning state of the system. Maintenance excellence is the balance between performance and risk, therefore this helps improve the sustainability of production. Traditionally, maintenance decisions are taken based on human experience and on the basic information known about the system. With the availability of data collected during the system's life cycle; machine learning approaches can help develop optimal strategies for maintenance actions. This paper proposes and depicts an optimization model imported from the machine learning field and developed to find optimal preventive maintenance strategies. The main objective of this developed optimization model is to minimize the downtime and allow the system to take autonomous decisions. In this work, the maintenance strategy is modeled as a Markov Decision Process (MDP). MDP is a classical forming of sequential decision-making problem. Reinforcement learning (RL) model is then developed to solve the problem interactively. RL uses the MDP to define the interaction between the learning agent and the environment. The final output from this method in an optimal policy allows providing optimal actions in different situations.

Keywords

Preventive Maintenance, Systems Reliability, Reinforcement Learning, Markov Decision Process.

1 Introduction

1.1 Maintenance problem

The growing competitive environment in the manufacturing field forces different organizations to reduce their costs (Yacout, 2010). The two main expenditure sources that can be reduced, without any loss of the quality level, are the energy consumption cost and the maintenance cost. Proper maintenance can also lead to optimizing energy consumption. The main objective of maintenance excellence is to ensure the maximum reliability and availability of the system with the minimum cost and without affecting the production quality. Maintenance can be classified into corrective maintenance (CM) and preventive maintenance (PM). CM is the maintenance actions that take place when the failure of the system occurs, thus these actions are the result of failure and they aim to restore the system to specific conditions. PM is performed while the system is still operating; and considered as set of activities performed to retain the system in specific conditions. Several steps are needed to achieve PM, which are inspection, detection and prevention of anticipated failure (Wang, 2002).

In this paper, our main concern is obtaining optimal PM strategy to minimize the downtime of the system. For this type of PM, the component is replaced after a specific time T or after failure, depending on which occurs first (Shey-Huei, Griffith, & Nakagawa, 1995). Classically the optimal replacement time T^* is obtained by solving an optimization problem. An example that implements this concept is proposed in (AbdelHaleem & Yacout, 1998). It has been noted that the solution given by this method may lead to local optimal time to replace for the different components of the system (Stephane Barde, Yacout, & Shin, 2016). To overcome this limitation, RL has been used to provide data-driven optimized solutions that could outperform the classical optimization techniques.

1.2 Reinforcement Learning

RL is an area of machine learning algorithm that is concerned with the decision-making process. A software agent learns to take actions by interacting with a dynamic environment. The agent knowledge is enhanced by using a scaler value feedback, which is related to a reward function. The agent learns how to take actions that lead to maximizing this reward function (Wiering & Van Otterlo, 2012). Mapping from the situation (state) to an optimal action is the main output of the RL and it is in the form of optimal policy to be followed in different situations. RL is solving problems modeled as Markov decision processes (MDPs). Unlike dynamic programming, RL does not need the probability transitions matrix and does not perform full backups to solve problems (Sutton & Barto, 2011). RL algorithms are model-free; they use exploration and exploitation techniques, and interaction with the environment to provide the optimal actions in different situations.

Game theory and robotics are the most popular domains for RL (Sutton & Barto, 2011), the industrial field is one of the domains impacted by RL. Xanthopoulos, Kiatipis, Koulouriotis, and Stieger (2018) proposed an approach to obtain near-optimal control policy for production-maintenance joint based on reinforcement learning. The solution proposed in this paper aimed to minimize the sum of two conflicting objective functions: the average inventory level and the average number of backorders. Kuhnle, Jakubik, and Lanza (2019) addressed the optimization of an opportunistic maintenance schedule for parallel working machines. The aim of this paper was to reduce downtime and increase production output. Xiao, Hongwei, and Chao (2016) investigated the problem of scheduling maintenance for two different series machines to sustain a certain buffer level between the two machines. Mattila and Virtanen (2011) proposed a maintenance scheduling for a fleet of aircrafts. The main objective of this paper is how to select maintenance times for different aircraft to keep a high level of readiness of the aircrafts fleet. This situation takes place when the activities of the fleet are not planned a priori. Liu, Dong, Lv, and Ye (2019) proposed an optimized maintenance plan that considers restrictions related to the resources as the spare parts that are available in stock. Also, Compare, Bellani, Cobelli, and Zio (2018) treated the problems of gas turbine parts flow management by considering a preventive maintenance plan and stochastic failures of gas turbines. All the previous literature is related to assembly line scheduling, optimal inventory level and optimal maintenance production joint schedules. Some limited literature refers to the use of RL to optimize maintenance plans only. Stephane Barde et al. (2016) proposed optimized preventive maintenance strategies for a fleet of military trucks. Three different preventive maintenance strategies were optimized using Monte Carlo reinforcement learning methods (MRCL). Also Stephane Barde, Shin, and Yacout (2016) proposed another solution to optimize opportunistic preventive maintenance for a multi-component system with a hierarchical structure. The optimized strategy was obtained using temporal difference reinforcement learning algorithm SARSA(λ). Based on the literature review a variety of work has been proposed in the field of using RL with maintenance. Most of this work is directed towards scheduling production and maintenance times to reach a certain required level of inventory. A smaller portion of the proposed work focuses its efforts to optimize the preventive maintenance plans using RL techniques.

This paper presents a model to optimize PM strategies using RL. The main goal of this model is to minimize the downtime of the system through autonomous decisions based on data-driven machine learning techniques. The reward function is constructed in terms of system reliability. The reliability of the system is obtained using the Kaplan-Meier estimate, which is a nonparametric survival function. This model avoids the limitations related to the parameters needed as inputs for traditional optimization methods like the renewal reward theory. The rest of this paper is organized as follow: section 2 provides a description of the problem and the proposed solution. Section 3 contains a numerical example. Conclusions and future work are presented in section 4.

2 Model Description

2.1 Problem description

Maintenance plans that aim to maintain the equipment in a functioning state are looking for maintenance excellence. As mentioned balancing maintenance excellence is a challenging task, since to ensure high performance or reliability levels for systems, maintenance actions should be performed regularly and within short periods. These frequent maintenance activities have high costs related to spare parts cost, labor cost and cost due to loss of availability. To solve this problem a compromise is needed. Most of the PM plans addressed this compromise by using the renewal reward theory. This theory proposes an explicit form to solve this compromise (Blischke & Murthy, 2003). AbdelHaleem and Yacout (1998) proposed a preventive maintenance strategy for a fleet of military trucks based on the renewal theory. The replacement time for each component is obtained by the renewal reward theory. The objective of this work was to obtain the optimal replacement time that minimizes the downtime of the system. The main limitation of this method is that many parameters needed as input to the model. In addition, the obtained solution is dependent on the inputs and any small change in the values of these parameters leads to different solutions. As an alternative, such limitations could be overcome by using the data collected during the equipment's life cycle to propose solutions based on machine learning. As maintenance is a decision-making problem, RL methods can be used to optimize maintenance strategies by using the data collected during the life cycle.

2.2 Reinforcement Learning Model

Model Description

In the proposed solution, a Markov decision process (MDP) is used to model the problem of searching for an optimal maintenance strategy. MDP is used since it is classical forming of sequential decision-making problem and RL uses it to define the interaction between the learning agent and the environment.

MDP has mainly the following four elements:

1. Discrete state space $\mathcal{S}$ in which, at every time step, a new state $s_t \in \mathcal{S}$ takes place.
2. A set of actions is available in action space $\mathcal{A}$, in which, at every time step, an action $a_t \in \mathcal{A}$ is taken.
3. Transition probabilities between the states $P(s_{t+1}|s_t, \mathrm{a}_t)$, which is the probability of being in state s_{t+1} given that the system was in state s_t and an action a_t is performed.
4. The reward function $r(s_t, a_t)$, which is the reward of performing an action a_t at state s_t. RL is capable of solving this MDP problem without the need for the transition probability matrix. A principal point in this modeling process is how the reward function is designed. The objective of this work is to minimize the system's downtime. That could be achieved through eliminating the failures by PM actions without exaggerate in the frequency of PM actions. Therefore, finding the optimal time for the PM actions is the solution to this problem. To fulfill these requirements without being restricted to use certain parameters, nonparametric estimation of the system $R(t)$ could be used for designing the reward function. Full description of the reward function is provided in the next section.

Model Formulation

As discussed, RL is a model-free concept, so there is no need for the transition probabilities matrix. The main elements that need to be defined are the states, the actions and the reward function. In the proposed model the system state is defined by the age G and W, which denotes the system status either normal $W=1$ or failure $W=0$. Then the following vector defines the equipment's state at any time:

$$s_t = (G_t, W_t). \quad (1)$$

The action at every time step can be either a PM action $a_t = 1$ or it may be "do-nothing" $a_t = 0$. The last element to be defined is the reward function $r(s_t, a_t)$. As discussed, the reward function design is proposed in nonparametric form. In addition, it should represent the objective of the model which is minimizing the downtime without introducing very frequent unnecessary PM actions. To achieve this compromise the following design for the reward function is proposed:

$$\mathrm{r}(s_t, \mathrm{a}_t) = \begin{cases} -R(t), & if\ \mathrm{a}_t = 1. \quad (2) \\ -1, & if\ \mathrm{a}_t = 0\ and\ \ W_{t+1} = 0. \quad (3) \\ R(t), & otherwise. \quad (4) \end{cases}$$

Equation (2) represents PM action before failure takes place. In this case, the reward that the agent receives has a small penalty with negative value of the reliability. This value is associated with the time when PM action is taken. The purpose of introducing this penalty aims to avoid any needless PM actions and encourage the agent to pick the right time for PM actions. Equation (3) represents the failure of the system before the PM action is taken. In this case, the agent is penalized by relatively large value, as the action that was selected by the agent lead to failure. Equation (4), $R(t)$ represents a positive value reward that the agent receives if no failure takes place and while no PM action is taken. As mentioned the value of $R(t)$ is obtained by Kaplan-Meier estimate which is a nonparametric survival function.

Solution Description

The objective of the RL is to find the best policy π that can maximize the expected reward r^* over an infinite time horizon as shown in equation (5):

$$r^* = {}^{max}_{\pi}\mathbb{E}[\textstyle\sum_{t=0}^{\infty} \gamma^t . r(s_{t,}\pi(a_t))|s_o]. \quad (5)$$

Where γ is the discount factor, $\gamma \in (0,1)$, and s_o is the initial state of the equipment.

The reward r depends on the actions that taken in the different states under a certain policy π. So, all the RL algorithms start by an arbitrary policy π and evaluate the state-action value function $Q(s, a)$ under π , then they keep improving the policy until reaching the optimal policy π^*. SARSA (λ) (State-Action-Reward-State-Action) algorithm is suitable in our case since it does not need to wait until the end of an episode to update the value of $Q(s, a)$. It just needs one step forward. Moreover, it provides fast convergence and it is not computationally expensive (Sutton & Barto, 2011). SRASA (λ) estimates the value function $Q(s, a)$ by using temporal-difference methods that are combined with eligibility traces. The value function $Q(s, a)$ is updated every transition from state-action pair to another. In this way, the value function is continuously updated. At the same time, policy π is keep updating towards π^* by using greedy approach. The update for the value function is done as shown in equation (6):

$$Q(s_t, \mathrm{a}_t) = Q(s_t, \mathrm{a}_t) + \gamma\ [\alpha. Q(s_{t+1}, \mathrm{a}_{t+1}) - Q(s_t, \mathrm{a}_t)]. \quad (6)$$

Where γ is the discount factor, $\gamma \in (0,1)$ and α is the learning rate, $\alpha \in (0,1)$.

The value function $Q(s, a)$ estimate provides the optimal policy π^*. Then π^* provides the optimal action to take at each state. Therefore, optimal time $T^*$for taking replacement action is obtained through this optimal policy π^*. The next section, section3, presents evaluation for the proposed model through a numerical example.

3 Model Evaluation

AbdelHaleem and Yacout (1998) proposed an optimized PM plan for a fleet of military trucks. The objective of the proposed plan is to minimize the downtime of the system. The optimal replacement time for each component was obtained by solving the optimization equation (7) that is based on the renewal theory.

$$argmin_{T^*}D = \frac{t_p\ .\ (1 - F(T) + t_f\ .\ F(T))}{(T + t_P)\ .\ (1 - F(T) + \left[\left(t_f + E[t|t\ \leq\ T]\right)\right].\ F(T)\ )} \quad (7)$$

Where T^* is the optimal replacement time to minimize the downtime D, t_p is the time to perform preventive maintenance action, t_f is the time for replacing the component in case of failure, $F(T)$ is the failure probability of component at time T and $E(t|t\leq T)$ is the expected time to failure given that failure happened before T. Failure data was gathered for all the components of the trucks and the failure probability distribution for each component was modeled by a Weibull cumulative density function then $T^*$was obtained for each component.

Two components, the brake, and the coupling are selected to evaluate the proposed model. The optimal replacement time T^* for the two components are obtained by the proposed model.

3.1 Finding the Optimal Replacement Time using the Proposed Model

In order to obtain the optimal replacement time T^* by the proposed model, MDP is used to model the problem of obtaining the optimal maintenance strategy. The proposed RL model solves the MDP without the need for the transition probability matrix. The Input for the proposed model is data in form of episodes; each episode consists of tuples of state, action and reward. The time step between every two tuples is 10 hrs, thus the age is defined for the state every 10 h also the decision is taken every 10 hrs. The state is defined by the age G and W which denotes the system status either normal $W=1$ or failure $W=0$. The actions at each state are either a PM action $a_t = 1$ or it may be "do-nothing" $a_t = 0$. The reward function is defined by the reliability $R(t)$. The reliability is obtained using the Kaplan-Meier estimate.

For the SARSA (λ) algorithm that solves the proposed model, the learning rate is selected to be 0.001. This learning rate is small enough to eliminate rough fluctuations if any noise appears on the data. The discounting factor is selected to be 0.6 to introduce an acceptable level of uncertainty about the actions in the future. Decaying exploration rate ϵ_n is used, $\epsilon_n = {}^{1}/_{(1+n)}$ where n is the n^{th} episode. The decaying exploration rate is used to ensure the convergence to the optimal solution (Sutton & Barto 2011). To define the size of data sample needed to train the SARSA (λ) algorithm, the average change in the value function $Q(s, a)$ is measured against the number of episodes. The required sample size can be defined as the number of episodes that lead to low and stable average change of $Q(s, a)$ (Sutton & Barto, 2011). As shown in figure 1, when using 10000 episodes or more the average change in $Q(s, a)$ is stable at value less than 0.05. Therefore, sample size of 10000 episodes is sufficient to be used for training SARSA (λ) algorithm to solve the model.

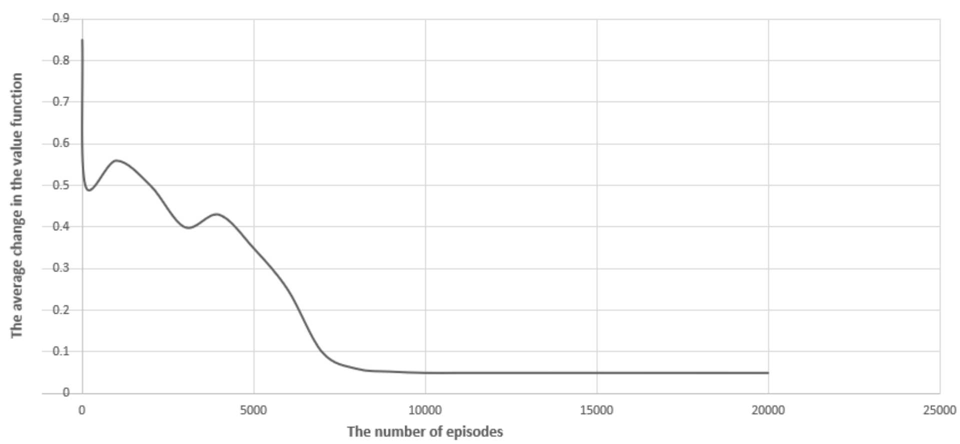

Figure 1 The average change in the value function versus the number of episodes.

3.2 Discrete event simulation

After obtaining T^* for the brake and the coupling, these values are compared with the values provided by AbdelHaleem and Yacout (1998). To complete the comparison a discrete event simulation for 100,000 hrs is performed. The simulation is performed using the optimal replacement time obtained by the two models to compare their performance. The simulation inputs are:

1. The optimal replacement time which defined by the proposed model and by the model of (AbdelHaleem & Yacout, 1998).
2. The time needed for PM action t_p and the time needed to correct a failure t_f are respectively 0.7 h and 3.5 h for the brake and .857 h and 6 h for the coupling.
3. The failure distribution function Weibull distribution $P(t; \lambda, k)$, for the brake $\lambda = 3933.12$, $k = 143.60$ and for the coupling $\lambda = 1406.84$, $k = 115.21$. All the parameters t_f, t_p, λ and k are obtained from (AbdelHaleem & Yacout, 1998) and Stephane Barde et al. (2016).

At each decision time, a random failure time (FT) is generated from the failure distribution function then:

1. If T^* > component age (G), then check if FT > G, then we move to the next step and the age of the component is increased by the time interval, while if FT < G, then the component is replaced, its age is reset to 0, the downtime is increased by t_f and 1 is added to the failure counter.
2. If $T^* < G$, then the component is replaced, its age is reset to 0, the downtime is increased by t_p and 1 is added to the replacement counter.

The outputs from this simulation are the total downtime of the equipment due to PM action or failure, the number of PM actions and the number of failures in 100000 hrs. Comparison and results are shown in table 1, table 2 and figure 2.

Table 1 Comparison between the results of the two models for the Brake.

	Brake			
	Optimal replacement time T^* hrs.	Number of PM actions	Number of Failures	Total Downtime hrs.
(AbdelHaleem & Yacout, 1998) Model	2250	444	0	310.8
Proposed Model	3800	261	2	189.7

Table 2 Comparison between the results of the two models for the Coupling

	Coupling			
	Optimal replacement time T^* hrs.	Number of PM actions	Number of Failures	Total Downtime hrs.
(AbdelHaleem & Yacout, 1998) Model	2160	0	715	4290
Proposed Model	1320	757	0	648.75

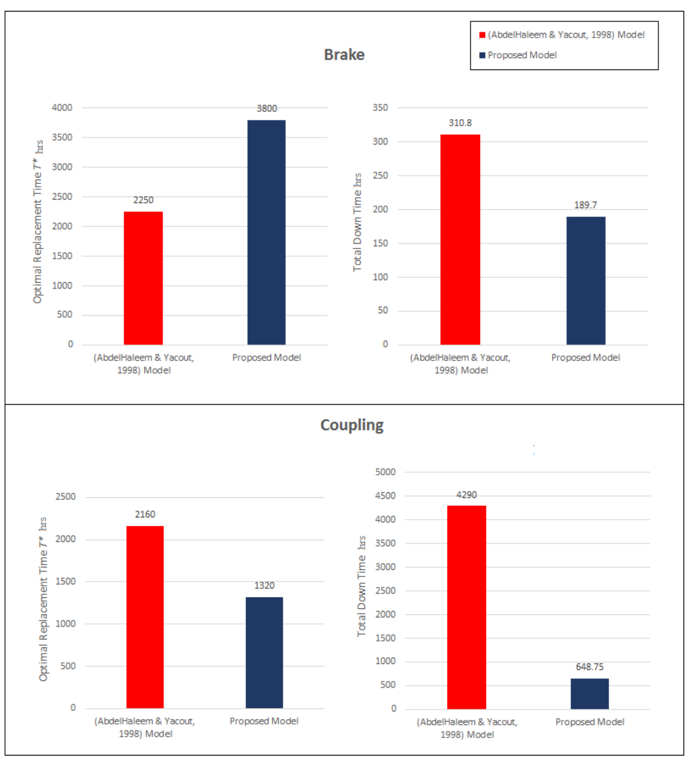

Figure 2 Simulation Results for the model by (AbdelHaleem & Yacout, 1998) and the proposed model.

3.3 Discussion of the Results

Figure 2, table 1 and table 2 show a comparison between the proposed model and the model by (AbdelHaleem & Yacout 1998). In terms of the optimal replacement time T^* the two models provide different results. For the brake T^*= 2250 hrs using the original model while by the proposed model T^*= 3800 hrs. For the coupling T^*= 2160 hrs by the original model while by the proposed model T^*= 1320 hrs. It is notable that in the brake's case T^* using the proposed model is bigger than T^* by the original model, while in the case of the coupling T^* by the proposed model is smaller than this by the original model. To investigate which of the two models having a better solution the discrete event simulation was performed using each solution. The results of the simulation show that the proposed model was able to outperform the original model by yielding lower downtime in both of the cases. For the brake, the downtime due to PM actions or failures correction is reduced by 39%. For the coupling a great reduction for the downtime by 84% took place. The interpretations of these results can be concluded as follows:

1. In case of the brake, the original model performed the PM actions with a high frequency which is not needed. These unneeded actions lead to increase the downtime. The proposed model found the value of T^* that eliminated the unneeded PM actions. A limitation appeared in the solution by the proposed model; that it allows two failures.
2. In the case of the coupling, the original model did not take any PM actions, it just corrected the failures. The proposed model obtained T^* that eliminated the failures to minimize the downtime.

From the previous interpretations, we could conclude the proposed model provides better performance than the original model. In addition, the proposed model is not dependent on any parameters.

4 Conclusions

The objective of this work aimed to find an optimal PM strategy, using RL area imported from the machine learning. This maintenance strategy minimizes the downtime of the systems. The proposed solution in this work to this problem is to develop RL model that could be solved by SARSA (λ) algorithm. First, the challenges related to the maintenance problem are described with the limitations of the available models. Mainly these limitations are both the need and the high dependency of the available models on the input parameters and their values. The proposed model overcomes this limitation. In the proposed solution the problem was modeled as MDP, the developed model was based on the reliability of the system. The Reliability was obtained using the Kaplan-Meier estimate. Then an optimal solution to the problem was founded by the SARSA(λ) algorithm. The problem was solved without the need for the transition probabilities matrix. In addition, the proposed model is not dependent on any parameters as the failure distribution function, t_p or t_f. These capabilities of RL as a nonparametric data-driven model enable it to solve real-time problem of autonomous decision-making.

To evaluate the performance of the proposed model, a numerical comparison between the original model and the proposed model through discrete event simulation was performed. The proposed model outperformed the original model in two different cases, as the proposed model provides T^* that yield less downtime when used to perform PM actions.

Areas for further research are: i. solve the limitation related to failure allowance as in case of the brake. ii. extend the model for the multicomponent systems, so all the components are considered together in the same model. iii. extend the model to include minimizing the maintenance cost explicitly in the objective.

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