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Heuristic optimisation for multi-asset intervention planning in a petrochemical plant

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Abstract

Large infrastructure assets commonly require high intervention costs, but the absence of an effective asset management plan can bring about a massive production loss for a company. Hence, managing these assets is considered a daunting task and is even more complicated if these assets operate collectively to produce an output. This paper explores a pragmatic approach to a multi-asset intervention scheduling problem through a case study of a vessel fleet in a petrochemical plant. After the relationship between the asset configuration and the system output is defined, an optimisation model with an objective to jointly minimise cost and risk is developed. Since the calculation of risk profiles across the fleet requires complex non-linear functions, a genetic algorithm is employed to search for an optimal combination of intervention schedules. Compared to the current run-to-failure strategy, the optimal strategy results in a significant reduction in system failure risk and a substantial improvement in long-term fleet conditions while reducing the total cost.

Keywords: Maintenance; Reliability; Multi-asset systems; Fleet; Optimisation; Genetic Algorithms.

1. Introduction

Intervention activities for large infrastructure assets generally require technical resource such as skilled workforce and specialised tools, thereby resulting in high intervention cost and considerable downtime. Realising a significant impact of an intervention decision on the system performance, academics and practitioners have devised numerous strategies to optimise inspection, repair, and replacement schedules for multi-asset systems in the past decades [1]. Traditionally, assets in a system are treated separately and the optimal intervention policy for each asset is developed

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in isolation [2]. Later researchers have become aware that multiple assets are not completely independent and therefore started to consider multiple assets as a whole and develop models that considers costs and risks across the system [3].

In a system of homogenous assets, maintenance scheduling problems generally emerge from two grounds. Firstly, there are insufficient maintenance facilities to serve assets in a system. Secondly, some systems necessitate that a minimum number of assets be in operational conditions, leading to joint maintenance and job assignment problems. Typical assets considered in these problems are vehicles (e.g. [4] and [5]) and industrial assets (e.g. [6] and [7]).

Previous studies demonstrate that equivalent intervention options can be applied to any asset in a fleet. Hence, only few criteria are required to measure the system performance. Prevalent objectives are to minimise the intervention cost and to maximise the system reliability. The main objective of a model is selected in line with the system value (performance, cost, and risk) perceived by a decision maker. For instance, Haghani and Shafahi [8] developed a model that maximises bus fleet availability, while Liang et al. [9] put their emphasis on intervention costs when devising their scheduling policies for a repair shop problem. Later literature employed a value-based approach to optimise both objectives simultaneously [10].

However, it is a delicate task for the decision maker to prioritise multiple objectives for a multi-asset system in which both the intervention cost and the economic consequence of system dysfunction are substantial. In this case, the application of joint optimisation is also difficult as the configuration among assets is not explicit. This means that models for multi-component systems in which the relationship among components is clearly defined may not be compatible with multi-asset problems. For instance, a failure of a component in k-out-of-N:G system, which fails instantly if more than $N - k$ components fail [11] , has a distinct effect on the system output, while the effect of a dysfunctional asset on the output of a multi-asset system cannot be directly measured.

Hence, this paper aims to address the intervention scheduling problem of a multi-asset system with indistinct asset configuration. The novelty of this work is based on the characteristic that the system requires k functional assets to operate at its full capacity but encounters different levels of output loss if fewer than k assets are operational. After identifying the impact of dysfunctional assets on business disruption, this study develops an optimisation model that jointly minimises intervention cost and system-wide risk. To validate our proposed model, we employ a case study of a petrochemical effluent treatment system to demonstrate the optimal strategy.

The remainder of this paper is organised as follows. Section 2 provides the characteristics of the system under our consideration and formulates the optimisation model. Subsequently, the proposed model is validated in a real industrial setting and the concomitant results are presented in Section 3. Finally, Section 4 distils a summary of the key contents and discusses potential research areas.

2. The proposed approach

In this paper, we consider a system of identical assets that operate collectively to achieve a desired output. To operate at its full capacity, the system requires that at least k assets are in operational conditions at a time. The system does not completely fail even if the number of functional assets are fewer than k. In this case, the production loss is incurred in line with the number of unavailable assets. This means that the system is sensitive to the unavailability due to both asset failure and intervention downtime. In this system, two intervention options – repair and replacement – are available for each asset. The risk level of each asset at any time period is determined on a multi-state basis. To incorporate objectives to minimise cost and risk of production loss into our model, the latter is converted into a business disruption cost, which is calculated by multiplying the probability of production loss by a corresponding penalty cost. This conversion allows us to arrive at a single objective function of minimising the total cost – the summation of intervention and business disruption cost. The remainder of this section discusses assumptions and model formulation to address the problem.

2.1. Assumptions

Our proposed model is based on the following assumptions:

- The system requires that at least k out of N assets be in their operational conditions in order to satisfy the maximum demand.

- The system incurs a step-function penalty cost per unit time if there are fewer than k assets in operational conditions.
- Each intervention option has a fixed level of improvement on the Remaining Useful Life (RUL) of an asset.
- The time that an asset is unavailable is fixed for each intervention option.
- There are five possible risk levels (A – E) for each asset. Level A and E represents the worst and the best state of an asset respectively. The evaluation of asset risk level is based solely on the RUL.
- The deterioration rate of an asset depends solely on its age. That is, the deterioration incurred from usage is negligent and the RUL decreases by 1 per month.

2.2. Model formulation

Sets

V	=	Set of assets
I	=	Set of intervention options = {1, 2} where 1 and 2 correspond to repair and replacement respectively
T	=	Set of time in months
	=	Set of time in years
S	=	Set of states of asset failure risk = {1, 2, 3, 4, 5} where 1 and 5 correspond to A and E respectively
F	=	Set of possible number of unavailable assets

Parameters

N	=	The total number of assets in the system
k	=	The minimum number of assets required to be operational at all time for the system to perform its full operations
m_i	=	The amount of time that an asset is taken off-line to perform intervention option $i \in I$ (month)
p_i	=	Level of asset condition improvement made by intervention option $i \in I$ (RUL)
c_i	=	Cost of intervention option $i \in I$ (kGBP)
b_f	=	Penalty cost for business disruption if $f \in F$ assets are unavailable at a time (kGBP/month)
h_s	=	Minimum threshold of reaching failure risk $s \in S$ (RUL)
n_v	=	Current condition of asset $v \in V$ (RUL)
l_s	=	Probability of asset failure of state $s \in S$
z	=	Maximum number of full repair activities allowed in a year
τ	=	Discount rate for actual intervention costs (per month)
ς	=	Discount rate for penalty cost (per month)

Decision variable

$\delta_{v,i,t}$	=	A binary variable deciding whether asset $v \in V$ starts undergoing intervention option $i \in I$ at time $t \in T$

Auxiliary variables

$u_{v,t}$	=	Remaining useful life of asset $v \in V$ at time $t \in T$ (RUL)
$\alpha_{v,t}$	=	A binary variable indicating whether asset $v \in V$ is available at time $t \in T$ (= 1 if it is available, = 0 otherwise)
$e_{v,t}$	=	Remaining unavailable time for asset $v \in V$ at time $t \in T$ (month)
$r_{v,t}$	=	Failure risk (probability of asset failure) of asset $v \in V$ at time $t \in T$
w_t	=	System wide risk (probability of system failure) at time $t \in T$

Formulation

Objective function:

$$\text{Minimise} \quad \sum_{v\in V}\sum_{i\in I}\sum_{t\in T}\frac{c_i \cdot \delta_{v,i,t}}{(1+\tau)^t} + \sum_{f\in F}\sum_{t\in T}\frac{b_f \cdot P(X_t = f)}{(1+\varsigma)^t} \tag{1}$$

Subject to:

Remaining unavailable time (RUT):

$$e_{v,t} = e_{v,t-1} + (\sum_{i\in I} m_i \cdot \delta_{v,i,t}) - (1-\alpha_{v,t-1}) \qquad \forall v \in V, t \in T \tag{2}$$

Remaining useful life:

$$u_{v,t} = (1-\delta_{v,2,t})(u_{v,t-1} - \alpha_{v,t-1} + p_1 \cdot \delta_{v,1,t}) + p_2 \cdot \delta_{v,2,t} \qquad \forall v \in V, t \in T \tag{3}$$

Range of remaining useful life:

$$1 \le u_{v,t} \le p_2 \qquad \forall v \in V, t \in T \tag{4}$$

Asset availability:

$$\alpha_{v,t} = \begin{cases} 1 & \text{if } e_{v,t} = 0 \\ 0 & \text{otherwise} \end{cases} \qquad \forall v \in V, t \in T \tag{5}$$

Risk monitor:

$$r_{v,t} = 1 \text{ if } \alpha_{v,t} = 0 \qquad \forall v \in V, t \in T \tag{6}$$

$$r_{v,t} = l_s \text{ if } \alpha_{v,t} \ne 0 \text{ and } h_s \le u_{v,t} < h_{s+1} \qquad \forall v \in V, s \in \{1,2,3,4\}, t \in T \tag{7}$$

$$r_{v,t} = l_s \text{ if } \alpha_{v,t} \ne 0 \text{ and } u_{v,t} \ge h_s \qquad \forall v \in V, s \in \{5\}, t \in T \tag{8}$$

System wide risk:

$$w_t = P(X_t > N - k) \qquad \forall t \in T \tag{9}$$

The objective function (1) is the summation of the discounted intervention cost (term 1) and the discounted business disruption cost (term 2) throughout a considered horizon. It is noteworthy that the system-wide risk probability $P(X_t = f)$ is calculated in accordance with the reliability of a system of non-identical k-out-of-N independent units [12]. The non-identicalness is due to the probability of vessel failure changing over time [13]. The notation $P(X_t = f)$ represents the probability that exactly f vessels are unavailable at time t.

Equation (2) explains that the remaining unavailable time (RUT) of an asset in a month is calculated by adding the RUT of the previous month (term 1 on the RHS) by the amount of time required to take the asset off-line (term 2 on the RHS) if it undergoes an intervention activity. If the asset is currently unavailable, the unavailable time will decrease by one every period (term 3 on the RHS becomes -1) until its RUT reaches zero and the asset becomes available again.

The calculation of the RUL of an asset is described in Equation (3). The RHS of the equation has two main parts. The first part becomes active when no full repair takes place. The first part shows that the RUL of an asset decreases by one every period if the asset was in its operational condition in the previous period. The RUL increases when a patch repair takes place during the period considered. The second part is active if an asset undergoes a replacement in that period, reverting the asset to its brand-new condition. Possible values of RUL are bounded by Constraint (4).

The relationship between the asset availability and the remaining unavailable time is established in Equation (5). An asset is deemed available only if the RUT of that asset is 0.

Equations (6) – (8) show how the risk state of an asset is defined by RUL thresholds. The asset is considered in a risk state if the RUL of an asset is located between that minimum threshold of that state and the minimum threshold of the next state. This probability becomes 1 when an asset is unavailable.

Equation (9) is a function of the probability that the system encounters a production loss. According to the system characteristics explained above, this probability is equal to the probability that more than $N - k$ assets fail. Since the probability of each vessel failure changes over time, the calculation of the probability of the system failure is based on that of a system of non-identical k-out-of-N independent units.

3. Numerical results

In this section, we present a comparison study using a case study of effluent treatment system in a petrochemical plant. The system is comprised of seven vessels and requires that six vessels be in their operational conditions in order to perform at its full capacity. The results are presented in two scenarios: run-to-failure strategy and our proposed strategy. In the run-to-failure scenario, each vessel is replaced right before it is expected to fail. As for the proposed model, we formulate the model in MATLAB and employ the Genetic Algorithm (GA) to search for the optimal solution. In this demonstration, we further assume that each vessel has 12-month beginning age difference. To overcome the disadvantage of finite horizon optimisation model, we run the model using a 720-month (60-year) time span and obtain the results for a 480-month (40-year) horizon. We use this time span because all vessels in both scenarios will have been replaced by year 40. It is noteworthy that GA is a heuristic optimisation technique, therefore ensuring a local optimal solution and that MATLAB takes 1 hour 53 minutes to arrive at the optimal solution.

Intervention decisions suggested by the proposed model are displayed in Table 1, while the numerical results of both scenarios are summarised in Table 2. Fig. 1 depicts the conditions of seven vessels throughout the considered horizon. The risk profile of the overall system is presented in Fig. 2. Stacked bars for all costs incurred in both scenarios are displayed in Fig. 3.

Table 1. Intervention decisions suggested by the proposed model.

Asset	Intervention decisions	
	Repair	Replacement
Vessel 1	Year 4, 38	Year 26
Vessel 2	–	Year 25
Vessel 3	Year 15	Year 31
Vessel 4	Year 8, 15	Year 34
Vessel 5	Year 9	Year 30
Vessel 6	Year 5, 13	Year 38
Vessel 7	Year 40	Year 28

Table 2. Summary of numerical results

Results	Run-to-failure	Proposed model
Total repair cost (kGBP)	–	3150.00
Total replacement cost (kGBP)	5600.00	5600.00
Total penalty cost (kGBP)	3901.03	491.47
Total cost (kGBP)	9501.03	9241.47
System-wide risk		
Average	0.0923	0.0352
Std.	0.2008	0.0802
Max	0.7741	0.3650
Ending system RUL (months)	1477	1803

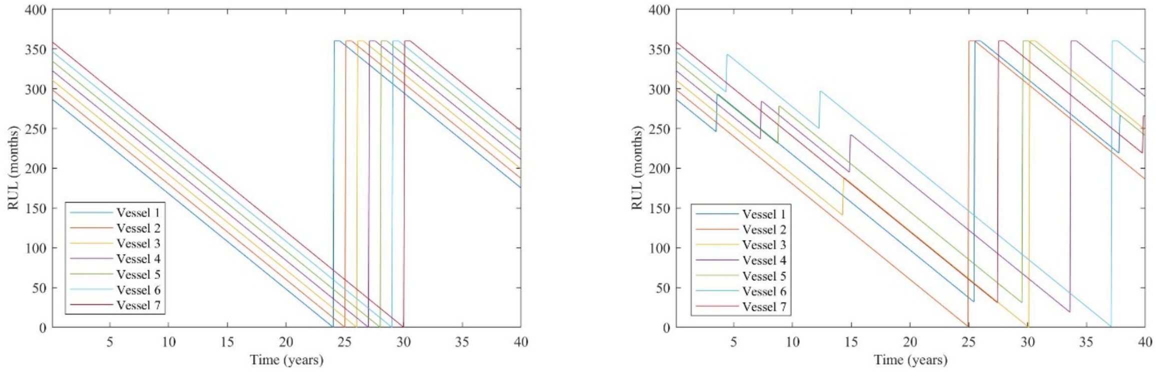

Fig. 1. Conditions of vessels resulted from (a) the run-to-failure strategy; (b) the proposed strategy.

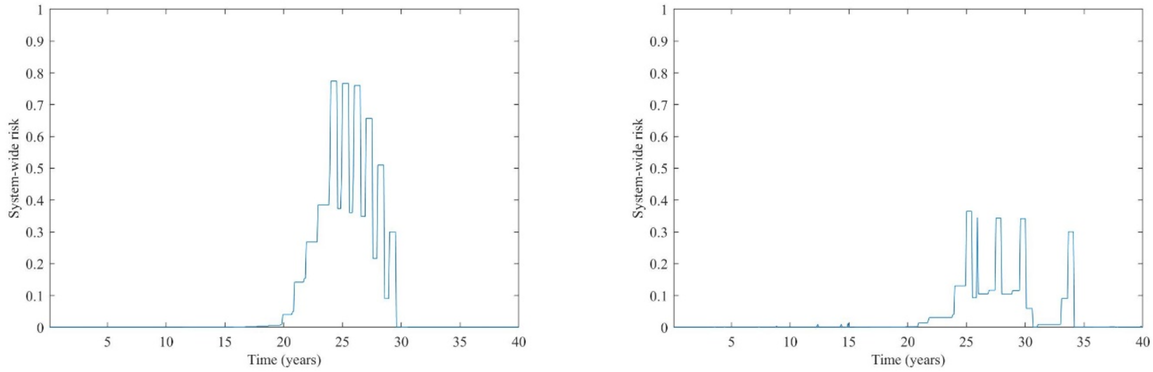

Fig. 2. Risk profiles resulted from (a) the run-to-failure strategy; (b) the proposed strategy.

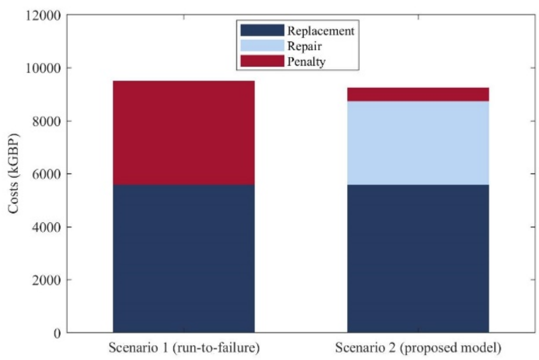

Fig. 3. Comparison of costs incurred in two scenarios

The results illustrate that the total cost incurred from our proposed model is slightly lower than that from the run-to-failure strategy. Moreover, the system also encounters significantly lower risks when the proposed model is employed. This can be seen from a smaller average failure probability and a more consistent risk figure (lower standard deviation) throughout the time span. Most importantly, in the proposed model, the summation of the ending RUL of all vessels after Year 40 (1803 RUL) is considerably higher than that obtained from the run-to-failure scenario (1477 RUL).

4. Conclusions and future work

This paper proposed an approach to modelling intervention planning for a multi-asset system by simultaneously optimising intervention costs and risks across the fleet. The case study of a system of homogeneous effluent treatment vessels bolstered the vital role that an effective intervention decision plays in minimising costs and preventing business disruptions. It was demonstrated that repair and replacement activities for large infrastructure assets are very costly and that the downtime due to these activities is significant. Due to the complexity of the fleet-wide risk calculation, we formulated our problem in a mixed-integer non-linear model and employed a genetic algorithm to search for an optimal solution. Compared to the run-to-failure strategy, the intervention policy suggested by our proposed model resulted in significantly low failure risk throughout the considered horizon while maintaining a small total cost.

Since our optimisation model is formulated in a way that it is solved heuristically, it is flexible and can be customised to deal with any complex constraint or deterioration function. Hence, future work will be directed towards the incorporation of a possible relationship among assets such as resource and economic dependence. Another suggested line of work is an extension of this model in order that it is compatible with systems of heterogeneous assets.

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