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Maintenance-based strategies for environmental risk minimization in the process industries

C.G. Vassiliadis, E.N. Pistikopoulos *

Centre for Process Systems Engineering, Department of Chemical Engineering, Imperial College of Science, Technology and Medicine, London SW7 2 BY, UK

Abstract

Industry, environmental agencies and the scientific community have all emphasized the need to include environmental impact considerations next to profitability objectives in the design phase of modern chemical processes, responding to the increasing social concern over environmental degradation in the past years. Most environmental impact assessment and minimization approaches, however, are rather qualitative, providing general guidelines. In this work, to overcome their limitations and rigorously represent the defining elements of environmental risk, i.e. the mechanism of occurrence of unexpected events usually related to equipment failure and the severity of their consequences, detailed process, reliability and maintenance characteristics are incorporated within a process optimization framework. The objective concerns the optimization of overall process performance defined as a system effectiveness vector characterized by both the environmental and the profitability functions of the system. Implementation of the framework on a process example identifies the optimal combination of process design and operation as well as preventive maintenance strategies that accomplish the conflicting environmental and profitability targets and quantifies the existing trade-offs between them. © 2000 Elsevier Science B.V. All rights reserved.

Keywords: Environmental risk; Non-routine releases; Optimization; Preventive maintenance; Process design; System effectiveness

1. Introduction

A major side-effect of modern chemical process technologies and products is the increase of damage to the environment due to industrial releases. Society, through regulating organisations, has responded to the growing concern over adverse environ-

* Corresponding author. Tel.: +44-171-5946620; fax: +44-171-5946606; e-mail: e.pistikopoulos@ic.ac.uk

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mental effects caused by major accidents by introducing strict legislative frameworks, such as the directive introduced by the European Commission after the Seveso incident in Northern Italy [1]. At the same time, significant effort has been directed from the industry, environmental agencies and the scientific community towards analysing a broad range of aspects and parameters related to environmental degradation. Walhstrom [2], commenting on the contribution of industrial releases (routine and accidental) to the possible loss of stability of nature's dynamic equilibrium, Pearce [3] studying previous industrial practices that led to environmental degradation and suggesting future policies for improvement, Patton [4] and Llewellyn [5] describing the main features required in methods for environmental risk assessment, all stretch the need to build mathematical modelling tools that globally assess the consequences of industrial releases and to design environmentally friendly process systems and products.

Environmental risk is associated with unplanned events through their probability and consequences and, hence, to minimize environmental risk both the probability and the consequences have to be minimized. Consequences relate to the physicochemical characteristics of process design and operation. On the other hand, the probability of unplanned events (e.g. component failure) depends on the impact of reliability and operability upon process design and operation.

Although most available methods dealing with environmental impact and risk are qualitative in nature (such as the utilization of checklists and networks, suggested by HMSO [6] or the hazard identification techniques — HAZOP and FMEA — in the works of Montague [7] and Christou [8]) and focused on post-release calculations, systematic and quantitative frameworks have started to appear [9].

To address the issue of integrating environmental impact assessment and minimization of routine releases (i.e. process effluent streams) in process design and operation, Pistikopoulos et al. [10] have introduced a methodology for environmental impact minimization (MEIM), the main steps of which include the following:

- definition of a process system boundary and emissions inventory
- environmental impact assessment
- incorporation of environmental impact criteria in process design objectives.

By embedding Life Cycle Analysis (LCA) principles within an optimisation framework comprising process specifications and environmental considerations, MEIM provides the best design alternative identifying the existing trade-offs between design economics and environmental impact.

Integrating environmental impact assessment techniques to incorporate risk related events and non-routine releases, Aelion et al. [11] have introduced the frequency/environmental load curve according to which they distinguish release scenarios depending on whether they result from intended or unintended plant operation and an estimate of accidental releases load is expressed as a function of the frequency of unexpected events (expected number of accidents per year) and the environmental load during each accident. Although an assessment framework, no explicit information is given on appropriate changes in process design and operation.

The fact, however, that non-routine releases concern deviations from planned operation and unexpected events such as equipment breakdown, leaks, etc. suggests that in order to be kept to an acceptable level, high *availability* must be achieved for the environmentally critical process units. Highlighting the importance of availability to the performance of the plant in terms of safety and environmental impact, new and tighter regulations are imposed on industry demanding for specific availability requirements of equipment and significant research work in the literature has been concerned with estimating the reliability levels of safety and regulator systems in process plants [12]. An analysis of contemporary techniques and future trends in the use of reliability engineering methodologies to facilitate safer operation of process plants can be found in the work of Michelsen [13]. Plant and unit availability is, by definition, a function of process and equipment *reliability* and *maintainability* the key elements of which (e.g. failure rate characteristics, storage tanks, redundancy and safety systems, system configuration and accessibility to components, etc.) are uniquely determined during the design phase of the process [14].

In the operating stage of the process, the way to achieve high equipment availability is through the derivation and execution of effective preventive maintenance strategies, such as inspection and replacement of critical units. Towards this direction we have witnessed an increasing interest in including environmental considerations and prioritizing maintenance activities with the objective to reduce environmental impact and risk. The benefits from employing a qualitative framework that considers environmental criteria to prioritize maintenance tasks in one of Exxon's chemical plants are reported in the work of Harnly [15]. Furthermore, Stefanis and Pistikopoulos [16] have recently extended the environmental impact assessment principles of MEIM to evaluate a criticality index for maintenance, ranking equipment components by the means of the effect their failure would have on process environmental performance. On the other hand, since maintenance in the chemical process industry is very expensive approaching 30% of all operating costs [17], maintenance optimization is traditionally defined as identifying the maintenance policy that optimizes the balance between maintenance costs and benefits [18], the latter concerning both the minimization of environmental risk and the maximization of process profitability. Considering, also, the fact that both environmental impact and process profitability are influenced by the existing uncertainty in a large number of process parameters and models [4,19], the need for a rigorous integrated framework to account for environmental impact considerations in conjunction with the complex interactions between different operability characteristics, such as flexibility, reliability and maintenance, at the very early design stage of the process has been strongly emphasized [20,21]. This is the scope of this work.

In Section 2, a *system effectiveness vector* is introduced, characterizing the performance of the process system, and the mathematical basis of our framework is presented. In Section 3, the trade-offs between maintenance costs, environmental risk and process revenue are quantified and presented by applying the proposed framework to a process example.

2. Mathematical foundations

The performance of a chemical process is a function of both process design and operation. Steady state operation is described by a mathematical model consisting of equality and inequality constraints of the following form:

$$h(d,z,x) = 0, \ g(d,z,x) \leq 0 \tag{1}$$

where

- d is the vector of design variables for the process (e.g. equipment volumes)
- z is the vector of degrees of freedom (e.g. split ratios, etc.)
- x is the vector of state variables (e.g. flowrates, pressures, temperatures, etc.).

Equality constraints (h) correspond to mass and energy balances and inequality constraints (g) correspond to process design and operation specifications. According to the design selection (d), the mathematical model in Eq. (1) forms a feasible operating region in which the degrees of freedom (z) can be manipulated to optimize process performance during operation. The feasible operating region for a specific design is defined as:

$$\mathrm{FOR}(d) = \left\{ (z,x) : \begin{Bmatrix} h(d,z,x) = 0 \\ g(d,z,x) \leq 0 \end{Bmatrix} \right\}. \tag{2}$$

Process performance is expressed both in terms of profitability and environmental behaviour. Environmental impact depends on the quantity and consequences of process releases, which in term of the mathematical model in Eq. (1) are represented by certain state variables whose values are determined by the decisions taken during operation within the feasible operating region provided by the selected process design. Therefore, in principal, an n-dimensional environmental impact vector can be defined as a function of the process variables and parameters:

$$\mathrm{EI} = f_1(d,z,x) \tag{3}$$

comprising n different indices which measure air pollution, water pollution, solid wastes, global warming, photochemical oxidation and stratospheric ozone depletion. Most of the existing environmental indices represent such relationships, such as the critical air mass index by Habersatter [22], used also in MEIM, as a measure of atmospheric damage of gas releases:

$$\mathrm{CTAM} = \sum_{w=1}^{W} \frac{\text{mass of emissions of } w\,(\text{kg mol } w/\text{h})}{\text{standard limit value}\,(\text{kg mol } w/\text{tn air})}, \tag{4}$$

where W is the set of released gases.

Process revenue depends on the sales of the end product which, in terms of the mathematical model, is also represented by a state variable (x) whose value again is determined by process operation (z) and design (d). Therefore, process revenue can also be expressed as:

$$\mathrm{REV} = f_2(d,z,x) \tag{5}$$

2.1. Modelling the mechanism of unexpected events

Non-routine releases are related to unexpected events, mostly accidents resulting from equipment breakdown. Concepts from discrete event theory, such as that of *state*,

state-space and *transition* can be used to model the mechanism of unexpected events, the occurrence of which is given by some time variant or invariant probability.

Consider a chemical system in steady-state operation whose components are all functioning properly. According to the operating programme, the impact of releases to the environment and the revenue of the process can be evaluated from expressions similar to Eqs. (1)–(3) and (5). If a failure occurs, the process model determining the operation changes according to which component has failed and, therefore, the values of environmental impact and process revenue change as well. The state of the system at time t is defined as (work of Cassandras [23]) the information required at t such as the output of the system is uniquely determined from this information and the input. Since the output of the system are the values of environmental impact and process revenue and the information required to determine them is what components are working and what not at time t, the state of the process system is defined as the set containing the operating status of each component. The occurrence of an unexpected event, such as equipment breakdown is represented by a transition from one state to another and all the possible states form the state-space of the system.

To gain some more insight, consider the chemical process in Fig. 1, which is typical of any industrial process, for the production of chemical C from reactant gases A, B and D (see also Ref. [16]). This process involves two reactors ([R-1] and [R-2]) where the reactions take place), two compressors ([CR-1] for the feed stream {A,B,D} and [CR-2] for recycling the gas mixture {A,B,C,D}), two mixers ([MX-1] and [MX-2]), two splitters ([SP-1] and [SP-2]) and a separation unit ([SEP]) for obtaining the end chemical product C. Such a chemical process is normally described by a mathematical model similar to the one in Eq. (1). The releases from the process correspond to the amount of gases A,B,C and D contained in the purge stream, as this is determined by the process model and operation and, hence, the environmental impact of the process is determined in a similar way to Eq. (3).

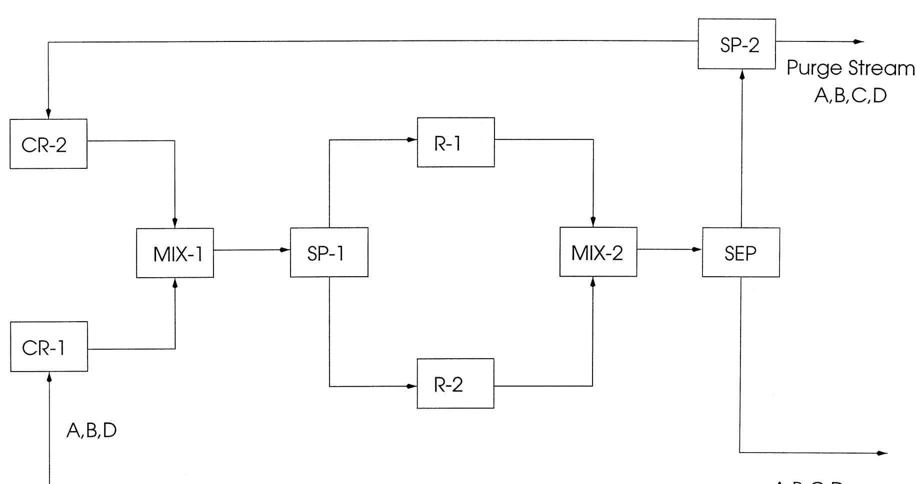

Fig. 1. Reaction-separation process.

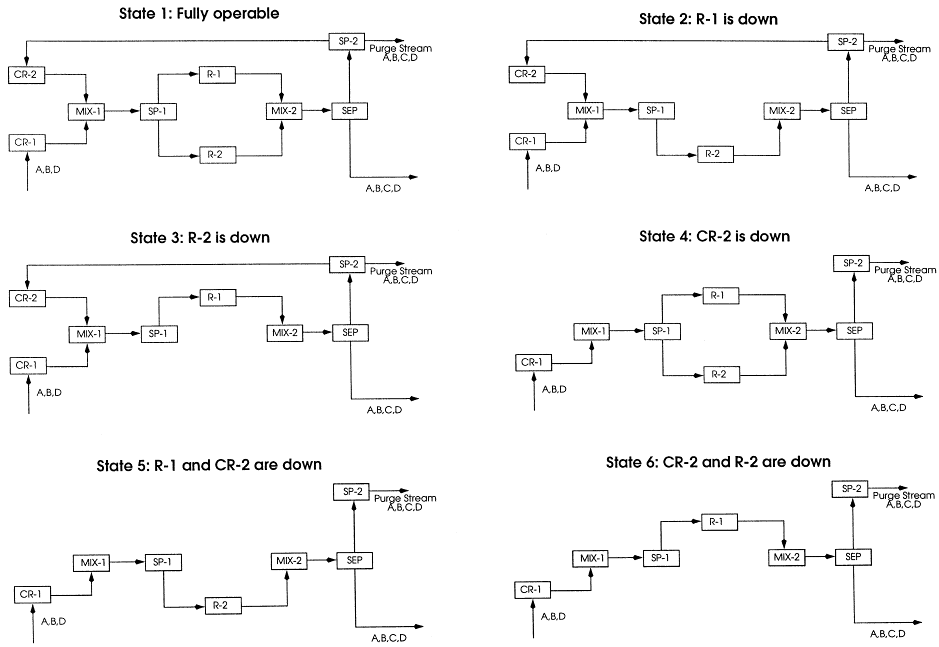

Fig. 2. Operable system states.

Adopting a state-space representation, this nine-component process is described by $2^9 = 612$ states in which the system may reside with possible degradation and failure of equipment. According to which units are functioning and which failed, the process can be in only one of the states at a time. From the complete state-space, however, only six states are *structurally operable*, meaning that only in six states the system can operate to produce chemical C. These states are depicted in Fig. 2 and can be formally identified from the structure function of the system or its minimal cuts (see, for example, Ref. [24]). Due to the change in system configuration because of failure, each operable state k is described by a different, in general, set of equality and inequality constraints determining a feasible operating region (FOR_k) which is defined as the set of all realizations of the degrees of freedom (z_k) for which feasible operation is guaranteed:

$$\mathrm{FOR}_k(d) = \left\{ (z_k, x_k) : \begin{Bmatrix} h_k(d, z_k, x_k) = 0 \\ g_k(d, z_k, x_k) \leq 0 \end{Bmatrix} \right\}, \forall k. \tag{6}$$

Furthermore, since the transitions between the states are related to equipment failure and repair, each state has a probability of occurrence which depends on the time-varying availability of each component determined by the reliability and maintainability characteristics of the equipment.

The new state equations h_k, g_k determine a new operating programme which, substituted in Eq. (3), yields a new value of environmental impact:

$$\mathrm{EI}_k = f_1(d, z_k, x_k), \forall k. \tag{7}$$

In the case of failure of the recycle compressor ([CR-2]), for example, the process model changes, the feasible operating region becomes smaller and the releases are expected to be much higher since nothing is recycled and everything escapes to the environment.

On the other hand, the revenue generated during operation is also a function of the system state and the mathematical model that describes it. Depending on the operation in state k, process revenue in that state is evaluated as:

$$\mathrm{REV}_k = f_2(d, z_k, x_k), \forall k \tag{8}$$

If, for example, one of the reactors fails the capacity of the process to produce the end product C decreases and the revenue of that state decreases accordingly.

It follows from the above that each state k, is characterised by its probability of occurrence $\mathrm{Pr}_k(t)$, its profit generating capacity and productivity $\mathrm{REV}_k(t)$, and the environmental impact caused during operation EI_k.

2.2. System effectiveness

Traditional reliability and maintenance practices, both during the design and the operation of the process aim at preventing the system from entering a failed state and maximizing availability. Not distinguishing, however, between the different levels of performance in different operable states and by treating operation as a binary event in which the system is simply either up or down, they fail to produce maintenance strategies that facilitate efficient process operation. Pyjadas and Chen [25], for example, underline that in the case of manufacturing systems, traditional reliability and maintenance design methods, focused on simply keeping equipment functioning, have produced poor results in terms of the profitability and environmental impact functions of the process. Going a step further, Grievink et al. [21] suggest that in order to overcome this drawback of current approaches, detailed process models (fully capturing physico-chemical characteristics) should be incorporated into reliability and maintenance design frameworks. In particular, they encourage the use of *system effectiveness* instead of a reliability-related criterion as an optimization objective.

System effectiveness depends on the probability of occurrence of each operable state k and the value of a process performance measure at this state (E_k), and is defined as their weighted sum:

$$E = \sum_k \mathrm{Pr}_k \cdot E_k. \tag{9}$$

In the case of the reaction-separation process in Fig. 1, performance is measured both in terms of environmental impact and profitability. Therefore, system effectiveness corresponds to an $(n+1)$ — dimensional vector consisting of an expected environmental impact vector and an expected revenue index ($E = \{\mathrm{EEI, ER}\}$). The expected environmental impact vector over a time horizon H of operation is defined as the weighted sum of the environmental impact generated when the process is operating in state k, using as weight the probability of the system being in that state:

$$\mathrm{EEI} = \int_0^H \sum_k \mathrm{Pr}_k(t) \mathrm{EI}_k \, \mathrm{d}t \tag{10}$$

and similarly is defined the expected revenue of the process:

$$\mathrm{ER} = \int_0^H \sum_k \mathrm{Pr}_k(t)\,\mathrm{REV}_k\,\mathrm{d}t. \tag{11}$$

Note that the environmental impact index EI_k and the revenue index REV_k in Eqs. (10) and (11) are determined, according to Eqs. (7) and (8), by the process physicochemical model, process design and process operation. On the other hand, the state probabilities $\mathrm{Pr}_k(t)$ are a function of the reliability and maintainability characteristics of the process. In particular, the implemented maintenance policy depends on the maintenance policy assumptions (e.g. age replacement, block replacement, etc.) and the maintenance optimization variables (maintenance intervals, number of maintenance activities for each component, sequence of maintenance actions, etc.). Therefore, in order to optimize the system effectiveness vector, both process design and operation, and reliability and maintenance design and implementation should be optimized accordingly.

2.3. Maintenance modelling issues

Eqs. (10) and (11) suggest that the system effectiveness vector is closely associated with the implemented maintenance policy, the defining elements of which are the assumptions regarding the type of maintenance that can be performed on the equipment and the maintenance variables regarding the derivation of preventive maintenance strategies.

The selection of the type of maintenance depends on the equipment attributes and specifications as well as the available maintenance facilities and capabilities. Different types of maintenance are defined both at a system level and at a component level. In the case of complex systems, for example, groups of components with similar operating conditions may be identified and treated uniformly during maintenance (e.g. group preventive maintenance policies). Furthermore, at a component level, assumptions are made regarding the effectiveness of maintenance in restoring the component to a good condition. As-Good-As-New (AGAN) policies, for example, restore the component to the original condition it was at the beginning of operation, while As-Good-As-Old (AGAO) policies bring it back to where it was immediately before the maintenance task started.

Maintenance optimization variables concern the elements of the maintenance policy that can be treated as decision variables to optimize a maintenance-related objective, commonly system availability. These variables usually regard the number of maintenance actions to be performed, the length of maintenance intervals, etc.

Depending on the nature and complexity of the assumptions and the desired level of detail and depth, different mathematical modelling tools have been employed in maintenance optimization frameworks, such as analytical techniques (e.g. the work of Vatn et al. [26]) and Markov decision processes (work of Gertsbakh [27]). In this work, an analytical approach is developed in which the probability of occurrence of each state — appearing in the system effectiveness vector and being the term that is determined by the maintenance strategy — is analytically expressed as a function of the maintenance optimization variables. Therefore, the identification of the reliability and maintenance characteristics that maximize system effectiveness shall be sought through the formulation and solution of an optimization problem.

2.3.1. An analytical technique

Consider a system with M components. Let $A_{1,j}(t)$ be the initial (before any maintenance is performed) reliability function of component j as a function of time. Let, also, t_1 and t_N denote the beginning and the end, respectively, of the time horizon of operation. The assumptions regarding the maintenance policy are the following:

- each time a maintenance action is to be performed, the type of maintenance is determined in the following way:
  - *corrective*, if the unit under maintenance is failed
  - *preventive*, if it is operable.

This assumption is common in the literature (e.g. the work of Tseng [28]) and valid in many real cases:

- all maintenance is of an AGAN type, i.e. the component is restored to its initial condition at the beginning of operation
- all failure events are independent
- one maintenance action is performed at a time.

The elements of the maintenance policy to be decided, i.e. the maintenance optimization variables, are the number of maintenance activities required for each component in the time horizon of operation, the sequence in which they will be performed and the exact maintenance time instants. For that purpose, the following optimization variables are introduced:

- N, which is an integer variable denoting the total number of maintenance activities
- t_λ, which is a continuous variable denoting the exact maintenance time instant of the $(\lambda-1)$th maintenance action
- $u_{\lambda,j}$, which is 0–1 variable depicting whether the $(\lambda-1)$th maintenance action will be performed on component j or on a different component and is defined as follows:

$$u_{\lambda j}=\begin{cases}1, & \text{if the } (\lambda-1)\text{th maintenance action is performed on unit } j\\ 0, & \text{if the } (\lambda-1)\text{th maintenance action is performed on a unit other than } j.\end{cases}$$

According to the assumptions made for the maintenance policy, analytical expressions are defined for the availability of the equipment and the expected duration of each maintenance task as a function of the maintenance optimization variables $(N,t_\lambda,u_{\lambda,j})$. From these, analytical expressions can be derived describing the probability of occurrence of each state k and, hence, the environmental risk and the profitability of the process as a function of the maintenance optimization variables. A detailed analysis on the derivation of such expressions can be found in Appendix A.

2.4. Optimization formulation

In this section, a multi-criteria optimization formulation (P1) is developed to identify the optimal design in terms of process characteristics and reliability and maintenance requirements, minimizing environmental risk and maximizing process profitability in a cost-effective way. For that purpose, two distinct objectives are included the first being the expected environmental risk and the second the expected process revenue subtracting investment and maintenance costs expressed analytically as functions of the design and the maintenance variables, respectively.

$$\min_{d,z_k,x_k,N,t_\lambda,u_{\lambda,j}} \int_{t_1}^{t_N} \sum_k \mathrm{Pr}_k(N,t_\lambda,u_{\lambda,j}) f_1(d,z_k,x_k)\mathrm{d}t \tag{P1}$$

$$\max_{d,z_k,x_k,N,t_\lambda,u_{\lambda,j}} \int_{t_1}^{t_N} \sum_k \mathrm{Pr}_k(N,t_\lambda,u_{\lambda,j}) f_2(d,z_k,x_k)\mathrm{d}t$$

design cost (d)

maintenance cost$(N,t_\lambda,u_{\lambda,j})$

s.t. process model(d,z_k,x_k)

maintenance constraints$(N,t_\lambda,u_{\lambda,j})$.

If environmental risk could be translated in terms of an operating cost then, in the context of a cost-benefit analysis, (P1) could be formulated having one objective with the advantage of identifying a unique solution, namely one optimal design, operating and maintenance policy. However, since in most cases it is not straightforward how to assign an economic value to environmental damage we will adopt the use of multiple independent criteria, one of which is going to be environmental risk as quantified using Eq. (10) and the machinery of MEIM.

In chemical process design, design costs are associated with the sizes of equipment components, normally through non-linear power law expressions [29]. The direct costs of maintenance are a function of the number of maintenance activities, the type of maintenance tasks and hence the cost of each maintenance task. The indirect costs of maintenance mainly relate to possible loss of production due to down time and repair and are incorporated in the objective function, as part of the expected revenue term. The process model represents the set of equality and inequality constraints defining the feasible operating region of each state k of the system. Maintenance constraints correspond to assumptions made when defining a maintenance policy and specific unit requirements. The exact form of (P1) can be found in Appendix A.

The solution of (P1) quantifies the trade-offs between the conflicting objectives and in the form of a pareto surface, it contains the complete set of optimal solutions for different values of design and maintenance costs, different requirements for profitability yielding different values of environmental risk. Therefore, the solution can be used as a road map to identify which are the available combinations of process design and operation strategies, as well as reliability and maintenance policies to achieve business targets within the legislation limits imposed for industrial releases.

3. Numerical example

Consider the reaction-separation process in Fig. 1. The process involves two reactors, R-1 and R-2 in parallel, where two isothermal reactions take place for the production of chemical C from reactant gases A, B and D according to a reaction scheme. The system

Table 1
Reliability and maintenance data

	a_j (10^{-4})	b_j (10^{-7})	τ_p	τ_c	C_p (10^4)	C_c (10^4)
CR-1	3.3	5	5	2	2	8
CR-2	3.3	5	5	2	2	8
MIX-1	1.8	3	4	1	1	5
SP-1	1.8	3	4	1	1	5
R-1	4.5	6	8	3	4	14
R-2	3.5	5.5	6	2.5	3	12
MIX-2	1.8	3	4	1	1	5
SEP	3	5.2	10	4	5	18
SP-2	1.8	3	4	1	1	5

also comprises a flash drum for the separation and two compressors (the main compressor CR-1 for the feed stream (A,B,D) and the recycle compressor CR-2 for the gas mixture (A,B,C,D). The chemicals that react in reactors R-1 and R-2 can be both from the feed stream and the stream that is recycled with compressor CR-2. The amount involved in each reaction is determined with a splitting decision (degree of freedom) at splitter SP-1. The volumes of the reactors (design variables) are considered fixed since, in this example, we want to focus on the interactions of maintenance policies and environmental risk. Formulation (P1), however, allows the identification of optimal process design out of several design alternatives and, therefore, we can also study possible process modifications and their impact upon environmental risk, process performance and maintenance costs. For the derivation of the optimal preventive maintenance policies, a time horizon $H = 1000$ is considered. A detailed mathematical model describing the physicochemical characteristics of the process can be found in the work of Stefanis and Pistikopoulos [16]. The reliability and maintenance specifications of the units are given in Table 1. The failure rate of each unit is assumed to increase linearly with time (equipment is in the wear-out phase), i.e., $q_j(t) = b_j \cdot t + a_j, \forall j$.

According to the amount of chemical C produced, a revenue is generated from the process and can be estimated from a revenue function in a similar to Eq. (5) way. The process, also, involves a purge stream (A,B,C,D) representing releases to the environment. The environmental impact of this releases can be determined using the Life Cycle Assessment techniques of MEIM. In particular, it is applied in the following steps: (a) *System boundary and emissions inventory*: The global boundary around the process is defined to allow for input–output waste interactions based on the LCA principles. The emissions inventory comprises chemicals A,B,C and D that are emitted through the purge stream in the fully operable state but can also cause significant environmental damage depending on whether critical equipment fails. (b) *Assessment of the environmental impact of releases*: The environmental impact of releases in each state k is quantified as:

$$\mathrm{EI}_k = \mathrm{CTAM}_k = \frac{F_A^k}{\mathrm{SLV_A}} + \frac{F_B^k}{\mathrm{SLV_B}} + \frac{F_B^k}{\mathrm{SLV_B}} + \frac{F_B^k}{\mathrm{SLV_B}}, \forall k \tag{12a}$$

Table 2
Environmental legislation limits

SLV_A	SLV_B	SLV_C	SLV_D
0.667	0.167	0.25	0.11

where F_w^k denoted the mass flowrate of each emission w at each state k and SLV_w (mol/tn air) its standard legislation value. These values are given in Table 2. Note that mass flowrates correspond to state variables (x_k) taking different values in each state according to the values of the degrees of freedom in that state (z_k: e.g. splitting ratio) and the design variables (d: equipment volumes). Therefore, CTAM is equivalent to $f_2(d,z,x)$ in Eq. (3).

In order to identify the optimal maintenance $(N,t_\lambda,u_{\lambda,j})$ and operating schemes (z_k,x_k) and depict the trade-offs between expected environmental impact, process revenue and maintenance cost (P1) is solved by employing a two-step solution strategy, as described in Appendix A.

3.1. *Trade-offs between environmental risk, process revenue and maintenance cost*

The complete set of optimal solutions forms the surface (Pareto surface), depicted in Fig. 3. Each point on the surface represents an optimal maintenance strategy $(N,t_\lambda,u_{\lambda,j})$

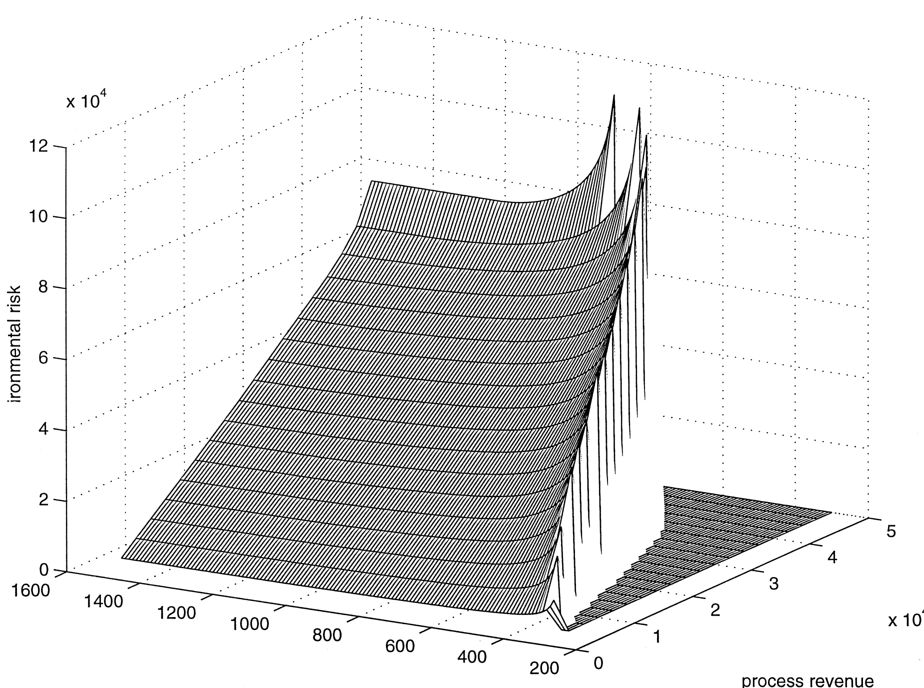

Fig. 3. Pareto surface of optimal solutions.

and an optimal operating policy (z_k, x_k) and the corresponding values for environmental risk, process revenue and maintenance cost. Therefore, optimal policies can be selected satisfying the requirements for the amount of releases allowed, for profitability targets and for maintenance expenditures.

3.2. Trade-offs between process revenue and maintenance cost

Suppose that environmental legislation suggests that environmental risk should be kept below 20,000. The bottom curve (EEI $\leq$ 20,000) in Fig. 4 depicts the set of optimal preventive maintenance schedules and operating programmes that keep environmental risk below 20,000. Note that the lower the maintenance costs the lower the expected revenue. This is due to the fact that since there is a hard environmental limit constraint, maintenance policies concentrate on providing more maintenance actions and, therefore, higher availability for the environmentally critical components (CR-2). Only if more maintenance resources are available (i.e. expensive policies to the right side of the *x*-coordinate), maintenance tasks are scheduled frequently for components that contribute primarily to the profitability of the process (e.g. R-1 and R-2). Furthermore, the strict environmental limit suggests that the amount of dangerous chemicals is decreased to avoid potential hazards and this reflects on the amount of end product produced.

On the other hand, when environmental limits are relaxed (EEI $\leq$ 50,000), the optimal solution suggests that certain maintenance tasks can be diverted from environmentally critical to profit contributing components. Furthermore, the amount of chemi-

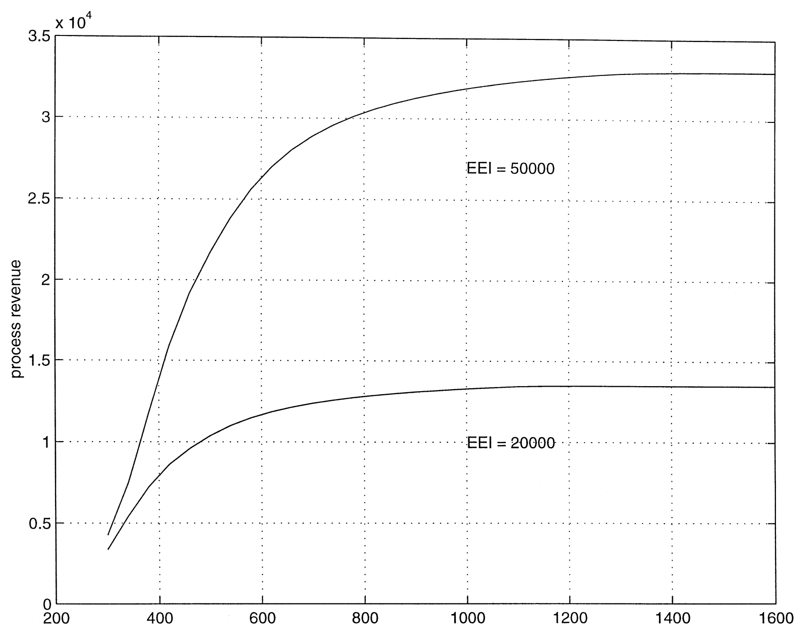

Fig. 4. Trade-offs between expected revenue and maintenance cost.

cals in the process is increased leading to an increase in profitability. This is depicted in the top curve in Fig. 4. Although similar trade-offs exist between process revenue and maintenance cost, for the same amount of maintenance and operating cost higher profitability is achieved (compare, for example, two points with the same maintenance costs on the two different curves).

3.3. Trade-offs between environmental risk and maintenance cost

Maintenance policies corresponding to the same value of process revenue present trade-offs between environmental risk values and maintenance cost. Consider, for example, the complete set of optimal solutions (i.e. operating and maintenance policies) depicted in Fig. 5, that keep profitability levels above 45,000. Since the top priority in this case is to meet the profitability target, all maintenance policies focus on maintaining as high as possible availability levels for the components that are critical to production. It takes higher budget maintenance policies (i.e. expensive policies to the right side of the x-coordinate) that can afford to assign enough maintenance tasks to provide high availability levels for environmentally-critical components (CR-2) as well in order to achieve lower values for environmental risk.

Take, for example, the point at the upper end of the curve which corresponds to the optimal maintenance policy with maintenance cost equal to 820 (optimal in the sense that it yields the minimum expected environmental impact that can be achieved from a maintenance policy that costs 820 and satisfies the process revenue target of 45,000).

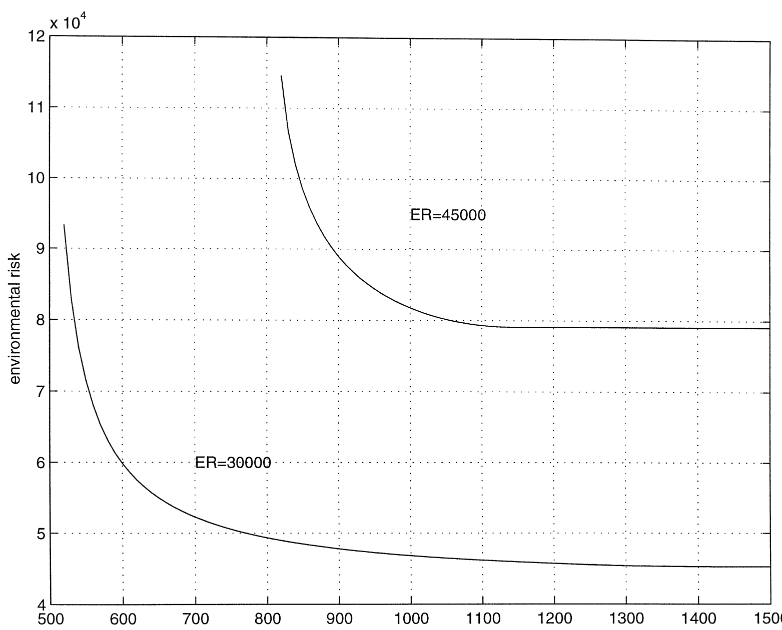

Fig. 5. Trade-offs between environmental risk and maintenance cost.

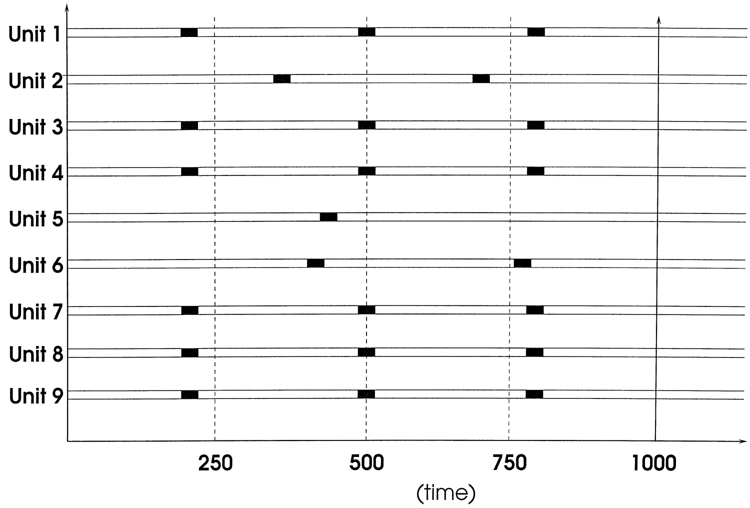

Fig. 6. Low-budget high-risk maintenance policy, expected revenue = 45,000.

This point corresponds to the preventive maintenance policy shown in Fig. 6. The implementation of this maintenance schedule would lead to an expected environmental impact of 114,500. A high budget maintenance policy (maintenance cost equal to 1100) on the lower end of the same curve (ER $\geq$ 45,000), on the other hand, involves a bigger number of maintenance tasks, many of which are directed towards the environmentally critical recycle compressor CR-2 (nine preventive maintenance tasks instead of two in the previous case). This is shown in Fig. 7. As a result, the probability of an accident is

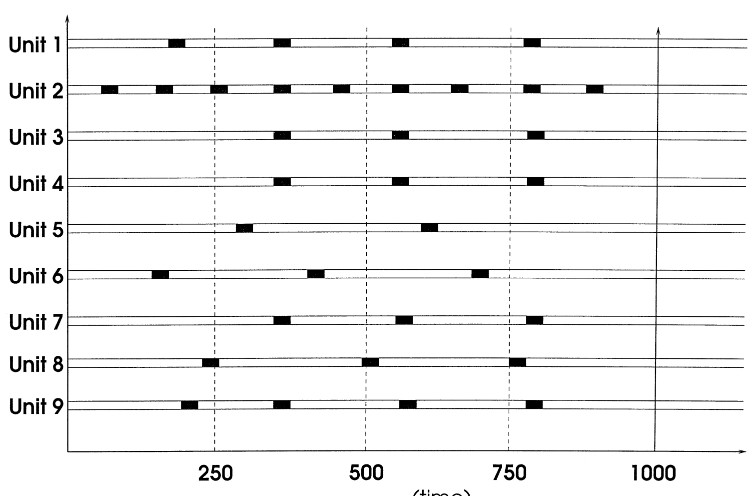

Fig. 7. Expensive low-risk maintenance policy, expected revenue = 45,000.

decreased and so is the expected environmental impact (EEI = 79,300). Despite the fact that all points on this curve (ER $\geq$ 45,000) correspond to maintenance policies that yield profit values larger than 45,000, the more expensive policies on the curve yield also lower environmental risk values since they can assign more maintenance tasks to environmentally critical components.

The same trade-offs between environmental risk and maintenance cost exist for lower profitability targets. This is confirmed by the curve which depicts the complete set of optimal maintenance and operating policies that produce an expected process revenue of 30,000. In this case, however, the expected environmental risk is generally lower and this is due to the fact that since less profit needs to be generated, less amounts of chemicals are used and produced and, therefore, the volume of releases both during steady state operation and in the case of an accident is smaller.

3.4. Trade-offs between environmental risk and process revenue

Fig. 8 depicts the trade-offs between environmental risk and process revenue for fixed maintenance cost maintenance policies. When there is a strict environmental limit to be met, most of the maintenance activities concern the environmentally critical components. On the other hand, when production volume is the objective and relatively high values of environmental risk are tolerable, maintenance tasks are scheduled more frequently for components that are more critical to profitability. To show this clearly, compare the preventive maintenance schedules, shown in Figs. 9 and 10, for two points

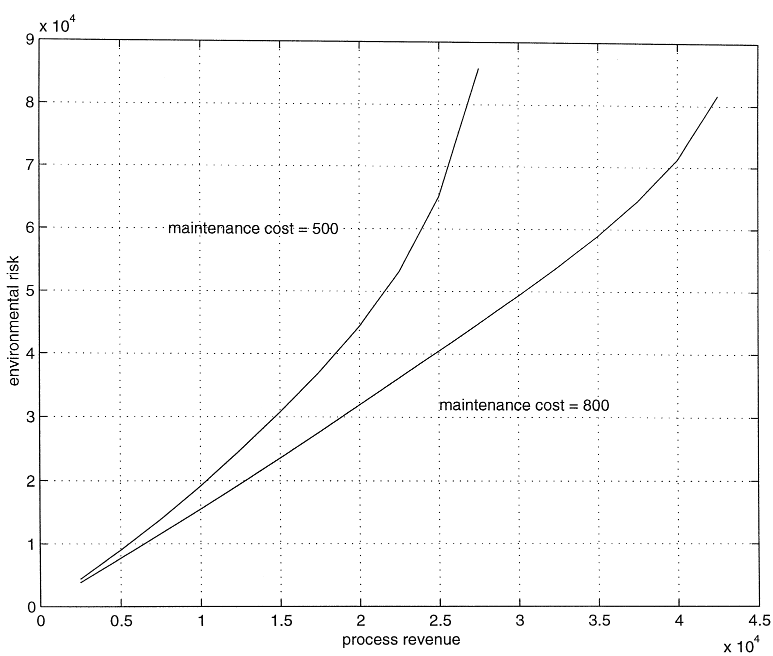

Fig. 8. Trade-offs between environmental risk and expected revenue.

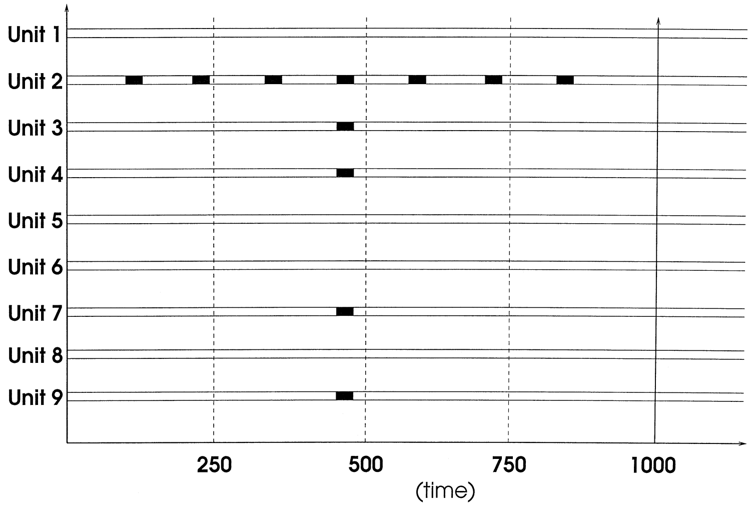

Fig. 9. Low-risk, low-profit maintenance policy, maintenance cost = 500.

at the lower and upper ends of the curve that represents the maintenance policies with cost equal to 500 (Fig. 8, maintenance cost = 500). Although both points correspond to maintenance policies that cost the same, the first policy concentrates on keeping the availability levels of the recycle compressor high since a strict environmental risk limit has been set EEI = 19,000 while the second maintenance schedule minimizes environmental risk after it has met the high profitability target (ER = 25,000). Note that the same trends are observed for different fixed values of maintenance costs, although the

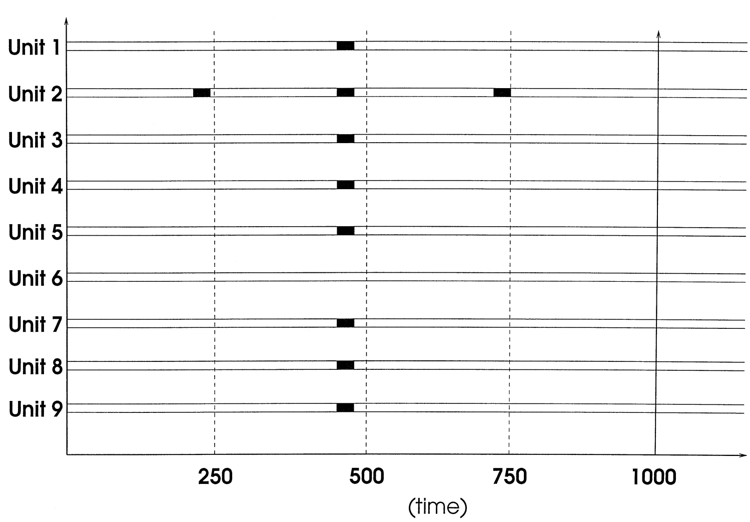

Fig. 10. High-risk, high-profit maintenance policy, maintenance cost = 500.

higher the maintenance cost, the bigger the expected production volume and the less the expected environmental impact that can be achieved (Fig. 8, maintenance cost = 800).

Note that the quantification of trade-offs between process revenue and environmental risk is not performed to suggest that the maximization of profit may be, in some ways, more favourable than the minimization of environmental risk. It is clear that such an analysis provides guidelines as to what maintenance and operating policies are needed to stay within the environmental legislation limits and maximize profitability.

Appendix A. Derivation of analytical expression for (P1)

A.1. Availability characteristics

The availability of each component j (probability that the component is up) *after* any maintenance action $(\lambda-1)$ taking place on some component in the system is $A_{\lambda,j})(t)=(1-u_{\lambda,j})A_{\lambda-1,j}(t)+u_{\lambda,j}A_{1,j}(t-t'_{\lambda})$, where $t'_{\lambda}=t_{\lambda}+\tau_{\lambda}$ is the end of maintenance action $(\lambda-1)$ and τ_{λ} is the expected duration of maintenance action $(\lambda-1)$. Therefore, the availability of component j after the first maintenance action is $A_{2,j}(t)=(1-u_{2,j})A_{1,j}(t)+u_{2,j}A_{1,j}(t-t'_1)$, after the second maintenance action is $A_{3,j}(t)=u_{3,j}A_{1,j}(t-t'_2)+u_{2,j}\cdot(1-u_{3,j})A_{1,j}(t-t'_1)+(1-u_{3,j})(1-u_{2,j})\cdot A_{1,j}(t)$ and, recursively, after the $(\lambda-1)$th maintenance action availability of component j is given by:

$$A_{\lambda,j}(t)=\sum_{k=1}^{\lambda}\left[\left(\prod_{i=k+1}^{\lambda}(1-u_{i,j})\right)u_{k,j}A_{1,j}(t-t'_k)\right],\ \forall\lambda,j. \tag{12b}$$

Similarly, the availability of each component j (probability that the component is up) *during* any maintenance action $(\lambda-1)$ taking place on some component in the system is $\bar{A}_{\lambda,j}(t)=(1-u_{\lambda,j})A_{\lambda-1}(t)$, suggesting that when the system is under maintenance, the availability of component j is zero, if this component is maintained, or it retains its availability characteristics, if maintenance is performed on another component. Recursively, during the $(\lambda-1)$th maintenance action availability of component j is given by:

$$\bar{A}_{\lambda,j}(t)=(1-u_{\lambda,j})\sum_{k=1}^{\lambda-1}\left[\left(\prod_{i=k+1}^{\lambda-1}(1-u_{i,j})\right)u_{k,j}A_{1,j}(t-t'_k)\right],\ \forall\lambda,j. \tag{13}$$

A.2. State probabilities

Due to the assumption of independent failures, the probability of a state k *after* any maintenance action $(\lambda-1)$ is:

$$P_{k,\lambda}(t)=\prod_{j\in \mathrm{OP}(k)}A_{\lambda,j}(t)\prod_{j\in\overline{\mathrm{OP}}(k)}\left(1-A_{\lambda,j}(t)\right),\ \forall k,\lambda \tag{14}$$

and the probability of occurrence of a state k *during* any maintenance action $(\lambda-1)$ is:

$$\bar{P}_{k,\lambda}(t)=\prod_{j\in \mathrm{OP}(k)}\bar{A}_{\lambda,j}(t)\prod_{j\in\overline{\mathrm{OP}}(k)}\left(1-\bar{A}_{\lambda,j}(t)\right),\ \forall k,\lambda \tag{15}$$

where $\mathrm{OP}(k)$ is the set of functioning components in state k.

A.3. Expected duration and cost of maintenance actions

The duration and cost of maintenance action $(\lambda - 1)$ depend on: (a) the unit that is maintained, (b) the duration and costs of preventive and corrective maintenance tasks, (τ_p, C_p) and (τ_c, C_c), respectively, and (c) whether the unit to be maintained is up at the time of maintenance t_λ (with probability $A_{\lambda-1,j}(t_\lambda)$), in which case preventive maintenance is performed, or down at the time of maintenance (with probability $1 - A_{\lambda-1,j}(t_\lambda)$), in which case corrective maintenance is performed.

Therefore, the expected duration of maintenance action $(\lambda - 1)$ is:

$$\tau_\lambda = \sum_{j=1}^{M} u_{\lambda,j}\left[A_{\lambda-1,j}(t_\lambda)\tau_p + \left(1 - A_{\lambda-1,j}(t_\lambda)\right)\tau_c \right], \forall\lambda \tag{16}$$

and the total expected cost of maintenance actions is:

$$\text{maintenance cost} = \sum_{\lambda=2}^{N} \sum_{j=1}^{M} u_{\lambda,j}\left[A_{\lambda-1,j}(t_\lambda) C_p + \left(1 - A_{\lambda-1,j}(t_\lambda)\right) C_c \right]. \tag{17}$$

A.4. Expected environmental risk

From Eqs. (10), (14)–(16), the expected environmental risk is:

$$\begin{aligned} \text{EEI} = & \sum_{\lambda-1}^{N-1} \int_{t_\lambda + \tau_\lambda}^{t_{\lambda+1}} \sum_{k \in S} P_{\lambda,k}(t) f_1(d, z_k, x_k) \mathrm{d}t \\ & + \sum_{\lambda-2}^{N-1} \int_{t_\lambda}^{t_\lambda + \tau_\lambda} \sum_{k \in S} \overline{P}_{\lambda,k}(t) f_1(d, z_k, x_k) \mathrm{d}t \end{aligned} \tag{18}$$

where the first term represents the environmental risk between maintenance actions while the second term represents the environmental risk during maintenance actions.

A.5. Expected revenue

From Eqs. (11), (14)–(16), the expected process revenue is:

$$\begin{aligned} \text{ER} = & \sum_{\lambda-1}^{N-1} \int_{t_\lambda + \tau_\lambda}^{t_{\lambda+1}} \sum_{k \in S} P_{\lambda,k}(t) f_2(d, z_k, x_k) \mathrm{d}t \\ & + \sum_{\lambda-2}^{N-1} \int_{t_\lambda}^{t_\lambda + \tau_\lambda} \sum_{k \in S} \overline{P}_{\lambda,k}(t) f_2(d, z_k, x_k) \mathrm{d}t. \end{aligned} \tag{19}$$

A.6. Optimization problem (P1)

By substituting Eqs. (12a), (12b), (13)–(19) in (P1), it can be rewritten as:

$$\begin{aligned} \min_{d, z_k, x_k, N, t_\lambda, u_{\lambda,j}} & \sum_{\lambda-1}^{N-1} \int_{t_\lambda + \tau_\lambda}^{t_{\lambda+1}} \sum_{k \in S} P_{\lambda,k}(t) f_1(d, z_k, x_k) \mathrm{d}t \\ & + \sum_{\lambda-2}^{N-1} \int_{t_\lambda}^{t_\lambda + \tau_\lambda} \sum_{k \in S} \overline{P}_{\lambda,k}(t) f_1(d, z_k, x_k) \mathrm{d}t \end{aligned}$$

$$\max_{d,z_k,x_k,N,t_\lambda,u_{\lambda,j}} \sum_{\lambda-1}^{N-1} \int_{t_\lambda+\tau_\lambda}^{t_{\lambda+1}} \sum_{k\in S} P_{\lambda,k}(t) f_2(d,z_k,x_k)\mathrm{d}t$$
$$+ \sum_{\lambda-2}^{N-1} \int_{t_\lambda}^{t_\lambda+\tau_\lambda} \sum_{k\in S} \overline{P}_{\lambda,k}(t) f_2(d,z_k,x_k)\mathrm{d}t$$
$$- \sum_{\lambda=2}^{N} \sum_{j=1}^{M} u_{\lambda,j}\left[A_{\lambda-1,j}(t_\lambda)C_\mathrm{p} + \left(1 - A_{\lambda-1,j}(t_\lambda)\right)C_\mathrm{c}\right] \tag{P1a}$$

design cost (d)

$$\textbf{s.t.}\ h_k(d,z_k,x_k) = 0,\ \forall k$$
$$g_k(d,z_k,x_k) \le 0,\ \forall k$$
$$\sum_{j=1}^{M} u_{\lambda,j} = 1,\ \forall\lambda \tag{20}$$
$$t_\lambda + \tau_\lambda \le t_{\lambda+1},\ \forall\lambda \tag{21}$$
$$\tau_\lambda = \sum_{j=1}^{M} u_{\lambda,j}\left[A_{\lambda-1,j}(t_\lambda)\tau_\mathrm{p} + \left(1 - A_{\lambda-1,j}(t_\lambda)\right)\tau_\mathrm{c}\right],\ \forall\lambda$$
$$P_{k,\lambda}(t) = \prod_{j\in \mathrm{OP}(k)} A_{\lambda,j}(t) \prod_{j\in \overline{\mathrm{OP}}(k)} \left(1 - A_{\lambda,j}(t)\right),\ \forall k,\lambda$$
$$\overline{P}_{k,\lambda}(t) = \prod_{j\in \mathrm{OP}(k)} \overline{A}_{\lambda,j}(t) \prod_{j\in \overline{\mathrm{OP}}(k)} \left(1 - \overline{A}_{\lambda,j}(t)\right),\ \forall k,\lambda$$
$$A_{\lambda,j}(t) = \sum_{k=1}^{\lambda}\left[\left(\prod_{i=k+1}^{\lambda}(1-u_{i,j})\right)u_{k,j}A_{1,j}(t-t'_k)\right],\ \forall\lambda,j$$
$$\overline{A}_{\lambda,j}(t) = (1-u_{\lambda,j})\sum_{k=1}^{\lambda-1}\left[\left(\prod_{i=k+1}^{\lambda-1}(1-u_{i,j})\right)u_{k,j}A_{1,j}(t-t'_k)\right],\ \forall\lambda,j.$$

Constraints 20 and 21 denote that one unit is maintained at a time and that the end of maintenance action $(\lambda-1)$ comes before the beginning of maintenance action λ.

Problem (P1a) involves: (a) highly non-linear terms in the 0–1 variables (e.g. $\sum_{k=1}^{\lambda}[(\prod_{i=k+1}^{\lambda}(1-u_{i,j}))u_{k,j}]$) for which simplifications and linearizations are not straightforward and may lead to a dramatic increase in the size of the problem, (b) combinatorial complexity. Therefore, it cannot be solved using one of the existing mixed-integer non-linear programming (MINLP) optimization algorithms. Furthermore, the presence of two objectives requires a transformation into a parametric MINLP to obtain a solution. A two-step solution strategy to solve (P1a) can be found in the work of Pistikopoulos and Vassiliadis [30].

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