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Industrial Environmental Performance Evaluation: A Markov-based Model Considering Data Uncertainty

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Abstract

Commonly, operational aspects of an industrial process are not included when evaluating the process environmental performance. These aspects are important as operational failures can intensify adverse environmental impacts or can diminish the chance of making any amelioration. This paper proposes to include these operational aspects by applying a method called Industrial Environmental Performance Evaluation. To have a reliable environmental performance measure for assisting policy-making in an organisation, two types of uncertainty are considered in the proposed method. The first type is the epistemic uncertainty due to imperfect knowledge about the environmental impacts of the process. Epistemic uncertainty is considered by using the potential probability of material release during operating and non-operating periods of the process. The second type is aleatory uncertainty due to potential stochastic behaviour of the process. Aleatory uncertainty is modelled through a Markov-based model and is considered by the state probability distribution vectors. The proposed method is employed to analyse an existing formaldehyde production process as a case study. The analysis shows the relation between environmental and operational performances of the process. Process owners can use this analysis for improving the environmental and operational aspects of their process and achieve accuracy in their environmental decisions.

Keywords: Decision-making, Environmental Model, Industrial Process, Maintenance, Markov Chain, Uncertainty.

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1. Introduction

An industrial process involves chemical and/or mechanical steps to manufacture finished goods from raw materials [Harmsen, 2004]. Environmental Performance Evaluation (EPE) methods are extensively used to quantify the environmental performance of industrial processes. Most of the em-

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Email addresses: `shokravi@unimelb.edu.au` (Samaneh Shokravi), `ajrs@unimelb.edu.au` (Alan J.R. Smith), `colb@unimelb.edu.au` (Colin R. Burvill) ployed EPE methods are based on techniques that were specifically designed for corporate performance evaluation. For instance, some of these techniques are Life Cycle Assessment/Analysis (LCA) [Dreyer et al., 2003; Bare and Gloria, 2005a; Finnveden et al., 2009; Gutierrez et al., 2010], Ecological Assessment [Chambers and Simmons, 2000a; Lenzen and Murray, 2001; Sarkis and Cordeiro, 2012], risk assessment [Paté-Cornell, 1987; Phimister et al., 2003; Lim et al., 2011] and Inherently Safer Design [Kletz, 1998; Srinivasan, 2006; Leon and Shariff, 2008] .

Due to the gap between the focus of these techniques and the application of the EPE methods built upon them in industrial processes, there are some shortcomings [Tyteca, 1995]. One of the shortcomings is that the majority of the used techniques only consider the materials, goods and chemical steps of the process and leave out the mechanical steps of the process. In general, input-output techniques, categorized by Shokravi [2013], consider inputs and outputs of the processes as input data for their model. This leads to ignoring the mechanical steps and the production units of an industrial process and consequently results in an incomplete and inaccurate environmental performance evaluation.

For instance, ecological assessment methods, or Ecological Footprint Analysis (EFA) [Lenzen and Murray, 2001; Huang et al., 2007], assess the relative environmental sustainability of competing technologies [Pollino et al., 2007] and provide an indicator for environmental performance evaluation [Dewulf, 2005]. Ecological assessment methods are based on the resource consumption trend [Herva et al., 2008] and the waste produced [Chambers and Simmons, 2000b; Herva et al., 2012b]. However, little is known about the time that it takes the waste to breakdown in the environment nor the overall impact of the waste in the interim [van Kooten and Bulte, 2000]. There is little overlap with issues associated with industrial processes and the issues that ecological assessment methods focus on. For example environmental impacts associated with industrial processes are overlooked in ecological assessment methods, such as toxicity of waste discharge and the impact of ozone depleting substances. As such ecological assessment methods such as EFA are well suited to raise social awareness about sustainability [van Kooten and Bulte, 2000] or screen environmental indicators [Herva et al., 2012a]. However, they do not have the necessary precision for use as environmental impact evaluation tools for industrial processes. Hence, the integration of ecological assessment methods with other methods, such as life cycle assessment [Herva and Roca, 2013] and environmental risk assessment [Herva et al., 2011], has been recommended.

Similar to EFA, LCA is one of the widely-used techniques that measures the environmental impacts of products and raw materials [AS/NZS ISO 14040, 2006]. LCA focuses on raw materials, goods and products, with a similar approach to that shown in Figure 1. LCA has been used for environmental impact assessments of process industries [Bare and Gloria, 2005b; Lim et al., 2011; Olsen et al., 2001]. In the last decade, some studies has been carried out to change the focus of LCA when assessing environmental impacts of industrial processes [Khan et al., 2002; Dreyer et al., 2003; Finnveden et al., 2009; Majumdar et al., 2009; Gutierrez et al., 2010]. For instance for industrial processes, Khan et al. [2002] proposed an environmental impact assessment, called *GreenPro-I*, that combines a risk-based LCA with fuzzy-based multi-criteria decision-making. Even though GreenPro-I focuses on products and materials in a similar manner to LCA, it models the imprecision of human perception as an *uncertainty* of human subjectivity through triangular fuzzy numbers [Khan et al., 2002].

According to Walker et al. [2003], the nature of uncertainty is categorized into *epistemic uncertainty* and *aleatory uncertainty*. Epistemic uncertainty is due to imperfect knowledge [Refsgaard et al., 2007] while aleatory uncertainty is due to inherent variability or potentially stochastic nature of the system/process [Rinderknecht et al., 2012]. Fuzzy-based techniques, for instance GreenPro-I [Khan et al., 2002] and other techniques by Nasiri and Huang [2008] and Tuzkaya et al. [2009], model the epistemic uncertainty. Whereas, aleatory uncertainty can be modelled through probability theory [Pollino et al., 2007; Chen and Pollino, 2012; Bastin et al., 2013]. For instance Probabilistic Risk Analysis [Paté-Cornell, 1996] considers aleatory uncertainty and uses ranking to calculate the environmental impacts [Sallak et al., 2013]. These ranks could easily vary from expert to expert or decision-maker to decision-maker [Hutchins and Sutherland, 2008]. In addition, the linear nature of ranking fails to capture the complex and perhaps non-linear aspects of environmental impacts.

Overall, current methods do not provide a complete evaluation of environmental performance for process industries considering the existing uncertainties associated with the data and the process. Therefore, an easy to understand measure is required that quantifies environmental impacts and accounts for the two sources of epistemic uncertainty and aleatory uncertainty, without relying on biased ranking.

The principal objective of this paper is to present a holistic Industrial Environmental Performance Evaluation (IEPE) for process industries. This paper: (i) provides an objective Environmental Perfor-

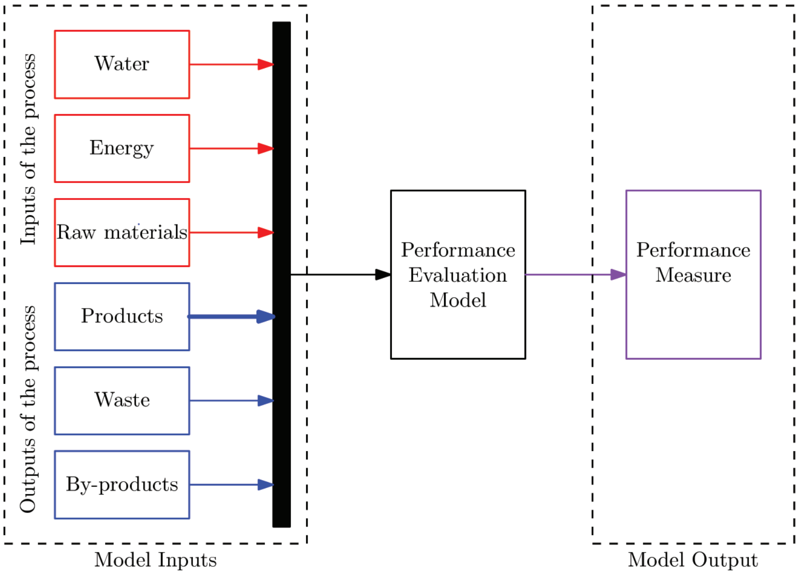

Figure 1: Considered parameters in input-output techniques for performance evaluation.

mance Parameter (*EPP*) that enfolds information about the whole industrial process including operating and non-operating states, (ii) considers the two types of uncertainties; the epistemic uncertainty is considered in the environmental impact calculation procedure and the aleatory uncertainty is allowed for through a multistate transition matrix and its probabilities, (iii) demonstrates that measuring the environmental performance of the process using its operational aspects integrates environmental and operational performances, and (iv) calculates environmental impacts without the need for biased ranking and scoring methods.

Section 2 of this paper begins by summarizing the objective of the proposed Industrial Environmental Performance Evaluation (IEPE) and presents the essential steps for implementing the proposed IEPE. Subsections 2.1 to 2.5 expand on these steps in detail. In Section 3, IEPE is used to evaluate a case study from the chemical industry sector as it is one of the most environmentally hazardous sectors [OECD, 2001], more diverse than virtually any other sector [National Academy of Engineering, 1999] and ubiquitous in the literature. Section 4 presents the results of the case study evaluation and discusses the findings. Section 5 concludes the paper with closing remarks and recommendations for further work.

2. Method

This section presents the details of the proposed method for evaluating industrial environmental performance, Industrial Environmental Performance Evaluation (IEPE) model. As illustrated in Figure 1, the conventional input-output performance evaluation methods consider two input categories. First, the inputs of the process, such as raw material, water and energy. Second, the outputs of the process, including the expected, unexpected and undesired products. This paper reports on the novel inclusion of a third category, as shown in Figure 2, that considers operational aspects of the process, which are the production units' failure history, the up-times and down-times of the process that correspond to the process availability, the environmental management system's targets and safety standards. Inclusion of operational aspects and mechanical steps of the process provides a more accurate performance measure for decision-making procedures.

After the IEPE inputs have been identified and the intent of the industrial process accepted, the proposed method may be divided into five distinct steps. These steps are expanded upon in Subsections 2.1 to 2.5.

Step 1- Divide the process into subprocesses. Identify each subprocess and define suitable operating and non-operating states for it (Subsection 2.1).

Step 2- For every state of each subprocess, calculate the impact function for every input and output, considering epistemic uncertainty (Subsection 2.2);

Step 3- For each subprocess, construct its unique multistate transition matrix by calculating the probabilities of changing to different states for a given time (Subsection 2.3);

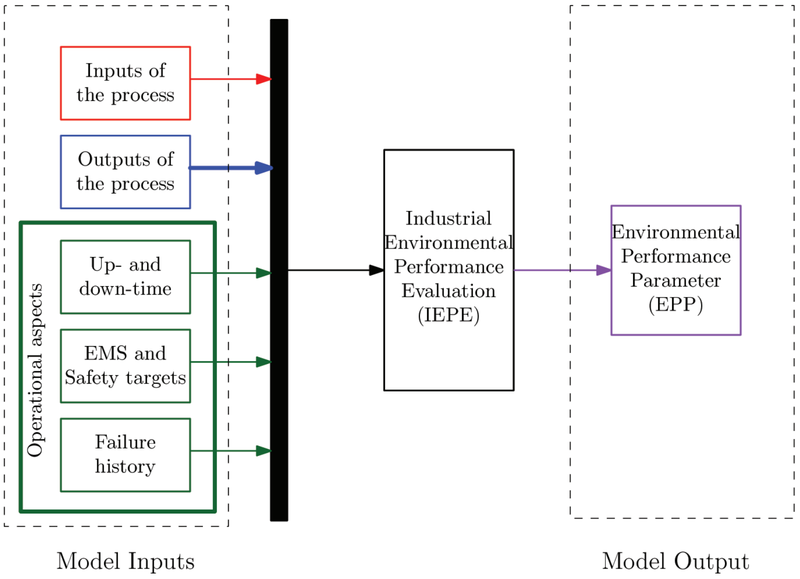

Figure 2: Model inputs and output for the proposed Industrial Environmental Performance Evaluation in this paper. EMS: Environmental Management System

Step 4- For each subprocess, characterize the aleatory uncertainty of the process by calculating the state probability distribution vector (Subsection 2.4);

Step 5- Calculate the expected value of Environmental Performance Parameter (EPP) for the industrial process by multiplying the impact function and the state probability distribution vector (Subsection 2.5).

Before describing these five steps in detail, made assumptions for these steps are presented. These assumptions assist with the modelling procedure of the industrial process and its complexities. Assumption 1 has been set regarding the timing and duration of the planned maintenance of the process:

Assumption 1. The transition to the planned maintenance state is periodic based on calendar time and happens at intervals of M time steps. At time $t = \imath M, \imath = 1, 2, ..., I$ all subprocesses in any state must transit to the planned maintenance state, where t represents time, $\imath$ is the counter for the planned maintenance intervals and I is the maximum number of planned maintenance states being considered in the model. At $t = \imath M + \Delta$, the subprocess transits from the planned maintenance state into the best operating state (where Δ is the duration of each planned maintenance state and $\Delta < M$). M and Δ for each subprocess are fixed numbers.

An unplanned outage state is defined for the subprocesses, as part of the first step (Section 2.1), and the reason for defining this state is:

Assumption 2. No subprocess can work indefinitely without failures. Random failures or age failures decrease the reliability ($R(t)$) of a subprocess, which is a non-increasing, continuous, monotonic function [Sahner et al., 1953].

After any kind of maintenance, unplanned or planned, it is assumed in this IEPE method that the subprocess transits to the best operating state, O_1. This is because it is assumed that:

Assumption 3. Repair is perfect, never damages anything and always restores the subprocess to As-Good-As-Before (AGAB) [Vassiliadis and Pistikopoulos, 2001], which means it is ready for the best possible level of operation with the highest yield.

At the start of the modelling process time, it is assumed that:

Assumption 4. The initial state for every subprocess is the best level of operation, O_1.

2.1. Identifying the Subprocesses

An industrial process is a dynamic entity that has operational properties and includes different operating and non-operating states. These states can include full capacity production, unplanned maintenance, unplanned outage and planned maintenance. A given industrial process is divided into subprocesses to model the operational aspects of the process, which are the production units' failure history, the up-times and down-times of the process that correspond to the process availability, the environmental management system's targets and the safety standards, in the defined states. Each subprocess can include one or more production units, for which inputs and outputs are identified. This approach not only models the inputs and outputs of the subprocess, but also includes the subprocess's failure rates. How the process is divided into its subprocesses is dependent on the need of the modeller, availability of the data and the decision-making procedure that will use the result of this evaluation. Subprocesses can occupy anyone of the defined states at a given time. The definition of these various states accommodates a probabilistic approach. This approach helps the modeller to consider the variability of the subprocess, or aleatory uncertainty, within the subprocess.

Considered states in this paper, (state denoted as s_t at time t), are: (1) Planned Maintenance ($s_t = PM$) is the scheduled maintenance and occurs based on calendar time[1]. (2) Unplanned Outage ($s_t = UO$) in which the subprocess has failed and is out of operation but repair has not yet begun. This could be due to technological or administrative delays, such as unidentified sources of failures. The start of UO is termed the start of *Time to Recovery*[2]. (3) Unplanned Maintenance and Repair ($s_t = UM$) in which the failed subprocess gets repaired. After the repair is completed the subprocess is operational. (4) The best operating state ($s_t = O_1$) is the best possible level of operation with the highest yield. (5) The middle operating state ($s_t = O_2$) is a condition between the best and the worst

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[1] Calendar time refers to how many hours of planned operation have passed, while operational time counts the number of hours in which the (sub)process has successfully operated.

[2] Time to Recovery is the period after the subprocess has failed until it is restored and operating [Pham, 2003]. Time to Recovery is divided into two states in this paper. First is UO state, in which the repair has not yet started. Second is UM state, in which the repair of the subprocess takes place.

with a middle level of yield. Finally, (6) the operation in the worst acceptable condition having the lowest yield ($s_t = O_3$). When it is not time for planned maintenance, at a given t, the possible transition between defined states is shown in Figure 3. Other states could be encountered, such as accidents and inspections with more or less hazardous impacts, respectively. These other states are not modelled in this paper, however they can be included if the modeller has sufficient information and believes the probability or impact of these other states is significant.

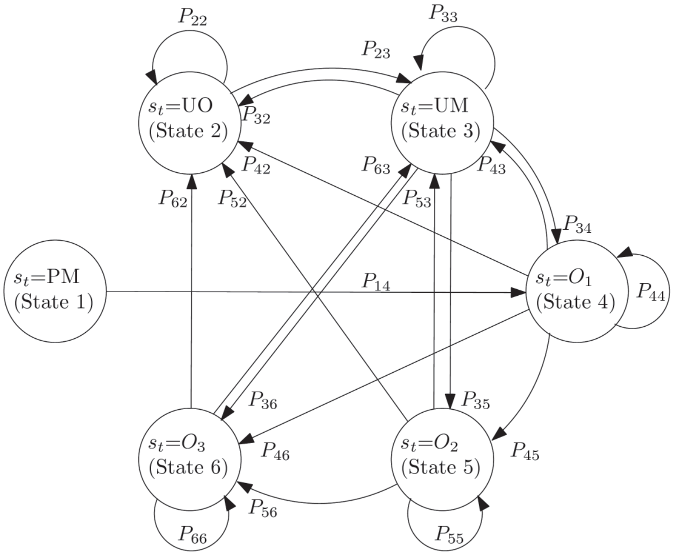

Figure 3: Different states that a subprocess can take at a given time in the proposed method when it is not time for planned maintenance. P_{ij}: transition probability between states i and j.

2.2. Calculating the Impact Function

In an ideal scenario, without physical and budgetary constraints, large quantities of data can be acquired about an industrial process and its environmental impacts by employing a large number of precise sensors; however, budget constraints reduce the number of available sensors. In addition, sensor precision has practical limitations. Therefore, the amount of collected information will be restricted. The uncertainty due to incomplete data collection is termed epistemic uncertainty [Walker et al., 2003]. In this paper, an Impact Function (IFu) is developed considering the epistemic uncertainty that is due to incomplete information about the process environmental impacts.

IFu consists of two variables, unitless environmental impact of material i (X_i) which calculates the environmental impacts of all the materials within the process; and normalized weighting for environmental impact of material i (ω_i) representing the importance of any given environmental impact according to the organisation/process Environmental Management System (EMS) and considered standards. These two variables are combined as shown in Equation 1. The epistemic uncertainty associated with some of the values used for calculating ω_i is considered based on imprecise probability theory. This consideration is further elaborated later in this section.

$$IFu = \sum_{i=1}^{N} X_i \times \omega_i \tag{1}$$

where N is the total number of materials (i) present in the process, including the raw materials, desired and undesired outputs that are products and wastes.

The environmental impacts of the raw materials, products and unexpected outputs, as well as wastes are considered within this model. In this paper, these impacts are categorized as air pollution, water pollution, soil pollution and resource depletion. The members of each category ($X_{u,i}$) are presented in Table 1, where u represents the number of subprocesses. Since the various environmental impacts have different dimensions or units, $X_{u,i}$ values need to be transformed into unitless numbers (X_i), for use in Equation 1. It is expected that any organisation seeking to evaluate its environmental performance will have a desire for continual improvement, as described in ISO standards for Environmental Management System (EMS). In the model, this is represented by a target value (S_{X_i}) being chosen such that it is lower than $X_{u,i}$. If the process does not comply with its local environmental protection agency (EPA) standards, every $X_{u,i}$ is divided by its permitted value according to EPA standards, as shown in Equation 2. When the process complies with EPA standards, the impact values are already equal to or lower than permitted values by EPA. Hence, the targets of the organisation's EMS are employed for calculation of Equation 2.

$$X_i = X_{u,i} / S_{X_i} \tag{2}$$

For some of the impact categories mentioned above, process materials must come into contact with the environment but the reason for this contact might not be known due to lack of data. The contact can be due to the normal operation of the process or associated with misbehaviour in the operation that leads to an unexpected material release. These sources of contact are defined by two types of weighting in this paper ($W_{i,1}$ and $W_{i,2}$) as shown in Equations 3 and 4, respectively.

$$W_{i,1} = (X_{u,i} - S_{X_i}) \,/\, (n_i \times X_{u,i}), \quad \text{only if } X_{u,i} \text{ is the impact from the process output} \tag{3}$$

$$W_{i,2} = (Y_i - S_{Y_i}) \,/\, (n_i \times Y_i), \quad \forall\, X_{u,i} \tag{4}$$

where n_i is the time (years) for material i to reach the EPA standard level or organisation's EMS target; Y_i is the release factor of material i and S_{y_i} is the organisation SMART target for a release factor of material i.

The first type ($W_{i,1}$ in Equation 3) represents the probability of an adverse effect from the process output on the environment, which happens when the product is produced. This type of weighting is calculated as the distance between the current value of the environmental impact and the future target or standard value that the organisation is trying to reach in n_i years (Equation 3). The future target

Table 1: The required equations and definitions associated with IFu for each subprocess.

Impacts	**Sub-impacts**	**Equation**	**Equation Reference**
Air pollution	Toxicity	$X_{1u,i} = LD_{50,i} + TLV_i \times ln(LC_{50,i})$	[Crowl and Louvar, 2001]
	Photochemical Smog	$X_{2u,i} = (0.75/6) \times [Prop - Equiv(i)](ozoneppb)$	[Hatakeyama et al., 1991]
		$[Prop - Equiv(i)] = PEC(i) \times \frac{k_{OH(i)}}{k_{OH(C_3\ H_6)}}$	[Hatakeyama et al., 1991]
	Acid Deposition	$X_{3u,i} = \frac{PEC_i}{CL_i}$	[Hatakeyama et al., 1991]
		$r_{mi} = \frac{1}{(H_i^* 3000)+100 f_{0,i}}$	[Wesely, 1989]
		$CL_i = 1624.7 r_{m,i} - 9.04$	[Gunasekera and Edwards, 2003]
	Global Warming	$X_{4u,i} = (Warming)_i \times\ Q_i$ (years $cm^{-2}\ atm^{-1}$)	[Verschueren, 1996]
		$(Warming)_i = \frac{\tau_i \times IR_{abs,i}}{MM_i}$	[Verschueren, 1996]
	Ozone Depletion	$X_{5u,i} = OD_i \times \frac{Q_i}{MM_i}$	[Verschueren, 1996]
		$OD_i = \tau_i \times (n_{Cl} + 30 n_{Br})$ (years $molecule^{-1}$)	[Verschueren, 1996]
Water Pollution	Heavy Metals	$X_{6u,i} =$ Quantity of the metal used	
	NOx	$X_{7u,i} =$ Quantity of NOx emitted	
Soil Pollution	Pesticides	$X_{8u,i} =$ Quantity of pesticides used	
	Fertilizers	$X_{9u,i} =$ Quantity of fertilizers used	
Resource Depletion	Water	$X_{10u,i} =$ Quantity of water used	
	Physical Material	$X_{11u,i} =$ Quantity of material used	
	Chemical Material	$X_{12u,i} =$ Quantity of chemical used	
	Natural Gas	$X_{13u,i} =$ Quantity of natural gas used	
	Oil	$X_{14u,i} =$ Quantity of oil used	
	Coal	$X_{15u,i} =$ Quantity of coal used	

PEC: Predicted Environmental Concentration

CL_i: Critical Level of material i

$f_{0,i}$: reactivity factor for oxidation of biological material i

H_i^*: Henry's law constant (M/atom) for material i

IR_i: Infrared Radiation for material i

$k_{OH(i)}$: the rate constant for the reaction between material i and OH radical

$k_{OH(C_3H_6)}$: the rate constant for the reaction between OH radical and propene

$LC_{50,i}$: lethal concentration of a material i after contact

$LD_{50,i}$: lethal dose of orally consumed material i

MM_i: Molecular Mass for material i

n_{Cl}: atmospheric lifetime of chlorine (Cl)

n_{Br}: atmospheric lifetime of barium (Br)

NOx: Nitrogen Oxide

OD_i: Ozone Depletion factor for material i

PEC_i: Predicted Environmental Concentration of material i

Prop-Equiv(i): concentration in parts per billion of propene required to yield a carbon oxidation rate equal to that of a volatile organic compound that is released into the atmosphere for material i

Q_i: Quantity of material i

$r_{m,i}$: mesophyllic resistance of material i

τ_i: the atmospheric life of material i

$X_{u,i}$: environmental impact of material i

values (S_{X_i}) are based on the EPA standards, other relevant standards or EMS targets.

The second type of weighting ($W_{i,2}$ in Equation 4) is associated with the probability of a material release during operation misbehaviour according to the process history. This type of weighting is concerned with the potential source that causes the release of material to the environment. These potential sources are called "release factors" in this paper. Release factors can be spills and leakage, human error and the low reliability of the hazard detection system. Y_i is the probability of release due to a specific release factor.

The knowledge for Y_i values is not complete and therefore it contains epistemic uncertainty. Therefore, to consider the existence of epistemic uncertainty in this model, imprecise probability theory is employed. According to [Borgonovo, 2008] for considering the epistemic uncertainty, imprecise probability is used by allocating minimum and maximum thresholds to the expected value of the probability.

In this paper, the minimum threshold for Y_i is the target value that the organisation is seeking to achieve. Whereas, the maximum threshold is the highest level that the organisation can tolerate. Recognizing the importance of continual improvement, this paper focuses on the use of minimum thresholds as specified in ISO 14000 series. Therefore, the second type of weighting is the difference between the probability of the release and its lower bound probability or minimum threshold, given by Equation 4. This weighting also represents the importance of a given environmental impact as the organisation is trying to decrease the gap between the current value of Y_i and its associated target in n_i years. The lower bound or future target of the process for the release factors are shown as S_{Y_i} in equation 4.

The influential release factors in each state can be different, for instance, human error is influential for non-operating states while the low reliability of the hazard detection system is calculated for the operating states. Therefore, the allocation of the appropriate release factor to each state is important.

Both weightings ($W_{i,1}$ and $W_{i,2}$) are normalized to allow calculations with smaller values. The normalized weightings (ω_i), which are given by Equation 5, are used for the IFu calculation in Equation 1. Appendix A presents a proof of the generality for the proposed IFu.

$$\omega_i = \frac{W_{i,j}}{\sum_{i=1}^{N} W_{i,j}}, \quad j = 1,2 \tag{5}$$

2.3. Establishing a Markov-based Model

In this step, a dynamic Markov-based model is proposed to deal with aleatory uncertainty. In order to characterize aleatory uncertainty, probabilistic approaches are employed [Rinderknecht et al., 2012]. Hence, the multistate transition matrix of the Markov-based model, $\prod(t)$ in Equation 6, and its transition probabilities are developed as the probabilistic approach in this paper. This model characterizes a dynamic version of the Markov chain. The value of transition probabilities between states O_1, O_2, O_3 and UO are not known. Hence, a series of functions using the failure rates of subprocesses are employed as the associated transition probabilities. These transition probabilities refer to degradation and failure of the subprocess as is elaborated later in this section.

$$\prod(t) = \begin{bmatrix} P_{11} & \dots & P_{16} \\ \vdots & \ddots & \vdots \\ P_{61} & \dots & P_{66} \end{bmatrix} \tag{6}$$

The proposed model considers the memoryless property of Markov chains. According to the memoryless property of Markov chains, the transition probability between two consecutive states depends only on the current state, but not how the previous state was reached. For further information about Markov chains refer to [Meyn et al., 2009].

According to Assumption 3 in Subsection 2.1, after planned maintenance every subprocess is in its best operating condition; that is, it transits from state one to state four. Hence, P_{14} is equal to one and the rest of the transition probabilities in the first row of the multistate transition matrix are zero.

The transition from Unplanned Outage (state two) to Planned Maintenance (state one) is based on calendar time, therefore it is equal to zero unless it is time for planned maintenance. Unplanned Outage, UO, is the state when the repair has not started for a failed subprocess. The transition probability from state two (UO) to state three (Unplanned Maintenance, UM) is the conditional probability $P(UM|UO) = h(t)$. Therefore:

$$P_{23} = P(UM|UO) = \frac{P(UM \cap UO)}{P(UO)} = P(t >= MTTR|t-1 =< MTTRe - MTTR) = h(t) \tag{7}$$

where $MTTRe$ is the average time between when the subprocess has failed and when it is restored and operating [Pham, 2003]. $MTTR$ is the average time of repair between when the repair action has started and when the failure of the subprocess is fixed. For a subprocess, if the distribution of the time to repair is known, Equation 7 can be calculated. Labovitz et al. [1999] and Lu et al. [1994] modelled the density function of the time to repair based on a Gamma distribution. A Gamma distribution is considered also for $h(t)$ in this paper.

In the second row of the transition matrix, staying in state two or transiting to state three are the only possible transitions. Hence, P_{22} and P_{23} values may be higher than zero ($P_{22} = 1 - P_{23}$). However, the other transition probabilities in the second row are equal to zero as failed subprocesses cannot transit to the operating states.

The third row of the transition matrix shows the probabilities of staying in the Unplanned Maintenance state or transiting from UM to the best operating state (O_1). This transition probability ($g(t)$) is a conditional probability as shown in Equation 8 and it is assumed to have a Gamma distribution:

$$P_{34} = P(O_1|UM) = \frac{P(O_1 \cap UM)}{P(UM)} = P(t > MTTR|t-1 =< MTTR) = g(t) \tag{8}$$

The fourth, fifth and sixth rows of the transition matrix follow a similar logic to the above. Moreover, the transition from a "worse" operating state to a "better" one is not allowed. Therefore, the transitions from states five and six to state four and from state six to state five are zero ($P_{54} = P_{64} = P_{65} = 0$). The transition probability of a subprocess from an operating state to the unplanned outage state is a function of the subprocess's failure rate. The transition from a better operating state (for example, O_1) to a worse one (i.e. O_2 or O_3) is a function of the failure rate. This function demonstrates the degradation of the subprocess. (The associated probabilities are presented in Appendix B). Therefore, by adding the influence of the failure rate to the transition matrix, Equation 6 becomes Equation 9. This equation presents two sets of values for $\prod(t)$. The first value is associated with the time when planned maintenance is not being performed ($t \notin [\imath M, \imath M + \Delta]$). The other value is valid during planned maintenance, and shows that during this time the subprocess transitions are to the Planned Maintenance state.

$$\prod(t) = \begin{cases} \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1-h(t) & h(t) & 0 & 0 & 0 \\ 0 & 0 & 1-g(t) & g(t) & 0 & 0 \\ 0 & \lambda_1 & 0 & (1-\lambda_1)\beta_1 & (1-\lambda_1)\beta_2 & (1-\lambda_1)\beta_3 \\ 0 & \lambda_2 & 0 & 0 & (1-\lambda_2)\gamma_1 & (1-\lambda_2)\gamma_2 \\ 0 & \lambda_3 & 0 & 0 & 0 & 1-\lambda_3 \end{bmatrix} & if\ t \notin [\imath M, \imath M + \Delta] \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} & \text{Otherwise} \end{cases} \tag{9}$$

where, λ is the failure rate of the subprocess. α_i, $i = 1,2$ and 3 are transition coefficients such that their summation is equal to one, the same is chosen for β_i, $i = 1,2$ and 3; and γ_j, $j = 1,2$. λ_i, $i = 1,2$ and 3 are the failure functions for three levels of operation, and $\lambda_1 = \alpha_1 \times \lambda$, $\lambda_2 = \alpha_2 \times \lambda$, $\lambda_3 = \alpha_3 \times \lambda$. The details of the transition coefficients are presented in Appendix C.

2.4. Characterizing the Aleatory Uncertainty

The aleatory uncertainty is associated with the stochastic nature of each subprocess. That is, the state of the subprocess cannot be known in advance. This means the state variable of each subprocess is random. To estimate the value of this random variable, a state probability distribution vector is determined. The state probability distribution vector uses the transition matrix of the Markov-based model and its memoryless property. Since aleatory uncertainty is irreducible [Oberkampf et al., 2004], the best way to deal with this uncertainty is to estimate the *likely* state of the subprocess at a given time, t.

Let $\mu(t)$ be the state probability distribution vector at time t, $\mu(t+1)$ for the next time step is calculated by Equation 10. The initial value of the state probability distribution vector is given by Equation 11, as Assumption 4 requires that the initial state for every subprocess to be state four (O_1).

$$\mu(t+1) = \mu(t) \times \prod(t) \quad \text{for } t = 1,2,\ldots n \tag{10}$$

$$\mu(1) = [0\;0\;0\;1\;0\;0] \tag{11}$$

2.5. *Calculating the EPP of the Process*

The final step of the proposed Industrial Environmental Performance Evaluation (IEPE) calculates the expected Environmental Performance Parameter (*EPP*) of the process by multiplying the impact functions and state probability distribution vectors of all subprocesses for all considered states. The value of impact function of every subprocess, IFu_u, is different for the various states (Equation 12). Based on the failure rate of the subprocesses, the probability of staying in and transiting to different levels of operation, the unplanned maintenance or unplanned outage states are different (Equation 13). Hence, each subprocess has its own transition matrix and its own state probability distribution vector at a given time. *EPP* is the expected value of the calculated IFu for the defined multistate process (Equation 14).

$$IFu_u = \Big[\; IFu(s_t = PM) \quad IFu(s_t = UO) \quad IFu(s_t = UM) \quad IFu(s_t = O_1) \quad IFu(s_t = O_2) \quad IFu(s_t = O_3) \;\Big]_u \tag{12}$$

$$\mu_u(t) = \Big[\; P(s_t = PM) \quad P(s_t = UO) \quad P(s_t = UM) \quad P(s_t = O_1) \quad P(s_t = O_2) \quad P(s_t = O_3) \;\Big]_u \tag{13}$$

where, $P(s_t)$ is the probability of being in state s_t.

$$EPP = \sum_{t=1}^{n} \left(\sum_{u=1}^{n_u} \left(\mu_u(t) \times IFu_u^{\top} \right) \right) \tag{14}$$

where n is the final time step, u is the identifier for subprocesses and n_u is the total number of subprocesses that the process has been divided into.

The determined *EPP* is a unitless number because IFu is unitless and $\mu(t)$ is a probability vector. In order to interpret the unitless *EPP*, a range $EPP_{min} \leq EPP \leq EPP_{max}$ is defined, where EPP_{min} and EPP_{max} are the to-be-determined minimum and maximum values of *EPP*, respectively. The *EPP* range is chosen for this model by considering the possible values associated with two parameters; the Planned Production Interval (*PPI*) and the Planned Maintenance Duration (*PMD*). *PPI* is the time between planned maintenance states and *PMD* is the expected time that it takes to carry out the planned maintenance.

It is proposed that EPP_{max} is determined by setting *PPI* to the process time and *PMD* to zero (i.e. there is no planned maintenance). This means that operation is planned to continue uninterrupted for the duration under consideration for the process. This arrangement yields the maximum EPP. The minimum EPP occurs when PMD lasts for a time step less than the whole process time and PPI is equal to a single time step of an hour. This value of PPI is chosen due to the fourth assumption that sets $\mu(1)$ equal to [0 0 0 1 0 0] and enforces the first state of any subprocess to be O_1. To facilitate the comparison between different duration and case scenarios, EPP of the process can be normalized utilizing to these maximum and minimum values (Equation 15):

$$EPP_{norm} = \frac{EPP - EPP_{min}}{EPP_{max} - EPP_{min}} \tag{15}$$

where, EPP_{norm} is the normalized environmental performance parameter.

When the calculated EPP is not the desired value according to the organisation's EMS, the process EPP can be changed through a number of approaches. These approaches include changes to the process design, the subprocess characteristics and the maintenance policy. This is elaborated more in discussion of the case study results presented in Section 4.

3. Case Study

The proposed Industrial Environmental Performance Evaluation (IEPE) method is applicable to various processes in different industry sectors. In this paper, a real-world formaldehyde production process is considered. One of the major products of the chemical industry in Australia is formaldehyde; contributing more than 60,000 tonnes in 2002 [NICNAS, 2006]. Formaldehyde is used primarily in the production of phenol- and urea-formaldehyde resins[3]. According to the UN classification of hazardous substances, formaldehyde is a class eight corrosive material that can destroy living tissue, steel and other materials on contact [ECOSOC Committee of Experts, 2005]. Also, formaldehyde is toxic by inhalation and a suspected carcinogen [Kirk and Othmer, 1994].

Subsections 3.1 to 3.5 implement the proposed IEPE by following the steps introduced in Subsections 2.1 to 2.5, respectively.

3.1. Identifying the Subprocesses

Formaldehyde (HCHO) can be produced using various chemical routes. In the illustrated route (Figure 4), methanol oxidation on a metallic oxide forms formaldehyde at a temperature in the range of 320 to 370°C ($CH_3OH + \frac{1}{2}O_2 \rightarrow HCHO + H_2O$). In order to implement the proposed IEPE method, the illustrated route is divided into five subprocesses, each associated with a single production unit.

The vaporizer in Figure 4 (subprocess 1) receives air and liquid methanol as inputs. Liquid methanol is sprayed into the input air stream through a spray nozzle ring in the vaporizer. The vaporizer produces vaporized methanol as its output. This vaporized methanol is received by a "reactor" that contains the metallic oxide catalyst (Subprocess 2 in Figure 4). A "heat exchanger" is the third

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[3] http://www.environment.gov.au/atmosphere/airquality/publications/sok/formaldehyde.html

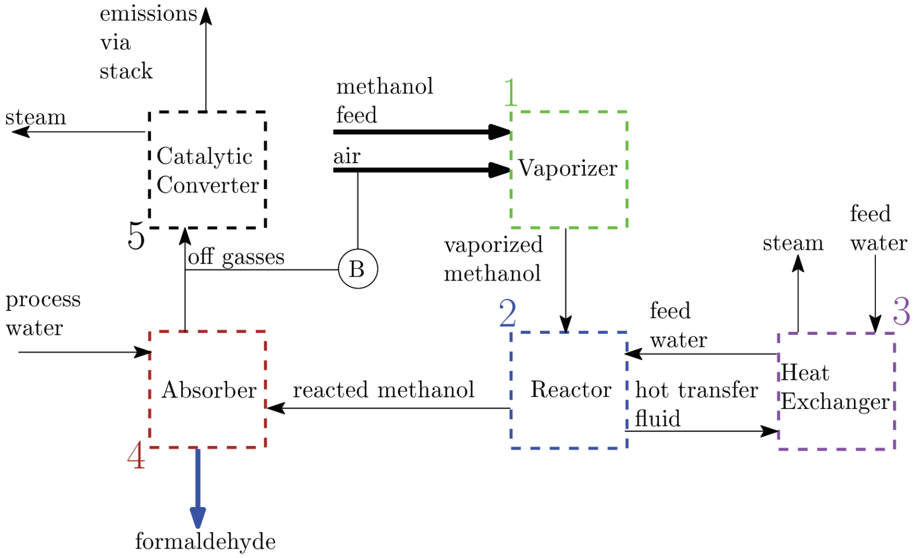

Figure 4: Formaldehyde production process with specified subprocesses that produces 54% formaldehyde (HCHO) [Kirk and Othmer, 1994, P 494]. B: Blower.

subprocess with hot transfer fluid (received from the reactor) and fresh feed water as inputs. The outputs of this subprocess are emitted steam and feed water. The reacted methanol from the reactor is sent to an "absorber" (Subprocess 4 in Figure 4). The absorber also receives process water to adjust the concentration of the produced formaldehyde. This production process produces formaldehyde with 54% purity. The absorber sends gaseous emissions to another subprocess that is a "catalyst converter". Some part of these emissions are harvested and added to the input air stream of the vaporizer. The possible formaldehyde gas in these emissions is meant to increase the efficiency of the process. The catalyst converter is an emission control system. It converts residual hydrocarbons and carbon monoxide into water and carbon dioxide. After the conversion, it emits the carbon dioxide to the air via a stack.

3.2. Calculating the Impact Function

Since liquid methanol is highly toxic, the first environmental impact considered for this process is the "toxicity of methanol". The first equation in Table 1 is used to calculate the toxicity impact. For methanol, $X_{1u,methanol}$ represents its toxicity impact, in which $LD_{50,methanol}$ is the lethal dose of orally consumed methanol that was found to kill 50% of experimental rats [EPA, 1994]. Threshold Limit Value for methanol, $TLV_{methanol}$, is the daily exposure for a human that does not cause adverse health effects [EPA, 1994]. $LC_{50,methanol}$ is the lethal concentration of the methanol that causes 50% of rats to die after being in contact under experimental conditions [EPA, 1994]. The critical values for various parameters of existing chemicals in this case study are shown in Table 2.

The influential release factors for the short term pollution impact of any chemical toxicity are human error, spills and leakage. Historical data are used to calculate the release factor weightings, based on EMS targets of the relevant organisation. Equations 3 and 4 are employed to calculate the weightings for the values of toxicity and other impacts. Equation 1 is used for calculating IFu for the various states. In order to make values unitless in Equation 2, this paper uses the rules of the Victorian Environment Protection Agency [2001, 2004, 1988]. Parameters for impacts and impact weighting calculations are presented in Tables 2 and 3.

Table 2: Constants associated with determining environmental impacts.

Parameter	**Value**	**Reference**
LC_{50} methanol	50,675,200 mg/m^3	HSDB[67-56-1]
LD_{50} methanol	4,456,250.4 mg/m^3	HSDB[67-56-1]
TWA methanol	262 mg/m^3	HSDB[67-56-1]
TWA formaldehyde	1.2 mg/m^3	HSDB[50-00-0]
LD_{50} formaldehyde	652,240 mg/m^3	HSDB[50-00-0]
LC_{50} formaldehyde	590 mg/m^3	HSDB[50-00-0]
PEC formaldehyde	$60-90\times10^{-9}\ m^3/mg$	HSDB[50-00-0]
TWA formic acid	9.4 mg/m^3	HSDB[50-00-0]
f_0 non-reactive	0	[Gunasekera and Edwards, 2003]
f_0 slightly reactive	0.1	[Gunasekera and Edwards, 2003]
f_0 highly reactive	1	[Gunasekera and Edwards, 2003]
$H^*_{methanol}$	230	[Butler and Ramchandani, 1935]
$H^*_{carbondioxide}$	2,400	[Gunasekera and Edwards, 2003]
$H^*_{carbonmonoxide}$	1,300	[Gunasekera and Edwards, 2003]
$H^*_{dimethylether}$	1	[Hine and Mookerjee, 1975]
$H^*_{formaldehyde}$	6,800	[Staudinger and Roberts, 1996]
τ : the atmospheric life of formaldehyde	2-20 days	HSDB[50-00-0]
MM: molecular mass of formaldehyde	30.03 $gmol^{-1}$	HSDB[50-00-0]

TWA: Time Weighted Average (One type of TLV)
HSDB: Hazardous Substances Data Bank: http://toxnet.nlm.nih.gov/cgi-bin/sis/htmlgen?HSDB

Table 3: Assumed and cited failure rate values for the illustrated case study.

#	**The release factor/subprocess**	**failure rate**	**Reference**
Y_1	human error	3.96E-4	assumed [Health and Safety Executives, 2012]
Y_2	spills and leakage	6.76E-4	assumed [Health and Safety Executives, 2012]
Y_3	gas detection system	2.63E-4	assumed [Health and Safety Executives, 2012]
Y_4	low-temperature detector	1.14E-4	assumed [Saignes, 2008]
Y_5	high-temperature detector	1.19E-4	assumed [Saignes, 2008]
Subprocess 1	Vaporizer	0.00255	[SINTEF Industrial Management, 2002, P 416]
Subprocess 2	Reactor	0.00155	[SINTEF Industrial Management, 2002, P 489]
Subprocess 3	Heat Exchanger	0.00456	[SINTEF Industrial Management, 2002, P 375]
Subprocess 4	Absorber	0.00524	[Bloch and Geitner, 1933]
Subprocess 5	Catalyst Converter	0.00365	[Bloch and Geitner, 1933]

3.3. Establishing a Markov-based Model

The novel application of a Markov-based model to calculating Environmental Performance Parameter (EPP) requires the rates at which subprocesses can transit from one state to another. The available data for the case study formaldehyde process only provides failure rates for the subprocesses. The various transition probabilities for a subprocess are generated using functions of its failure rate. For example, the multistate transition matrix of the vaporizer is given by Equation 16.

$$\prod_{Vaporizer} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0.00255\alpha_1 & 0 & \beta_1(1-0.00255\alpha_1) & \beta_2(1-0.00255\alpha_1) & \beta_3(1-0.00255\alpha_1) \\ 0 & 0.00255\alpha_2 & 0 & 0 & \gamma_1(1-0.00255\alpha_2) & \gamma_2(1-0.00255\alpha_2) \\ 0 & 0.00255\alpha_3 & 0 & 0 & 0 & 1-0.00255\alpha_3 \end{bmatrix} \tag{16}$$

where the transition coefficients are related as: $\alpha_1+\alpha_2+\alpha_3=1$, $\beta_1+\beta_2+\beta_3=1$ and $\gamma_1+\gamma_2=1$. In this case, the failure rates are given by single values in Table 3, for instance the nominated failure rate of the vaporizer is 0.00255. This indicates the failure functions are of an exponential type. Hence, for this case study the multistate transition matrices are static.

According to Assumption 3 the transition from the planned maintenance state during the operation time is always to the best operating state of O_1, hence in the first row of the matrix the fourth element is one. Due to the lack of information about the distribution of the $MTTR$ and $MTTRe$ in this case study, it is assumed that for the vaporizer the transitions between UO to UM and UM to O_1, P_{23} and P_{34}, only take one time step. This is assumed as the vaporizer has a relatively low failure rate and is easy to repair. The transition matrices for other subprocesses are presented in Appendix C.

3.4. Characterizing the Aleatory Uncertainty

The calculation of the state probability distribution vector, $\mu(t)$, follows from the memoryless property of the multistate transition matrix. Hence, $\mu(t+1)$ is calculated using Equation 17.

$$\mu(t+1) = \mu(t) \times \prod \quad \text{for} \quad t = 1, 2, \ldots, n \tag{17}$$

where n is the final process time step, and in this case study is equal to 8,760 which is the number of hours in a full year with 52 weeks, 7 days per week, 3 shifts per day, 8 hours per shift. The continuous operation for this case study is based on a real world formaldehyde plant. The initial state probability distribution vector is given by Equation 11.

3.5. Calculating the EPP of the Process

Any given process has a unique *EPP* related to its parameters. These parameters include duration of the process, design of the process, the failure rate of the subprocesses, maintenance schedule and maintenance strategies. In this paper, two parameters have been chosen. The first parameter is Planned Production Interval (*PPI*). For this case study, *PPI* is chosen to be between three and nine weeks with an increment rate of one week. The second parameter is Planned Maintenance Duration (*PMD*) between eight hours and five days with an increment rate of one shift (eight hours).

The algorithms corresponding to the five steps of the proposed Industrial Environmental Performance Evaluation (IEPE) method are included in Appendix D. The fourth algorithm representing the fifth step of the method employs the parameters of *PPI* and *PMD* to calculate a unique EPP. The calculated EPP for the tested range of these parameters results in a three dimensional array. The results for the implementation of the proposed IEPE of the formaldehyde production process are presented and discussed in the next section.

4. Results and Discussion

This section presents the results of the proposed IEPE and the analysis of the illustrated case study. To show the importance of having an accurate and reliable *EPP* for policy-making, the influence of variations in the transition probabilities and the subprocesses' failure rates have been modelled through three modelling alternatives. The production period and *EPP* are measured for these three modelling alternatives (Subsection 4.3). These modelling alternatives use an extreme case of reality to demonstrate the modular capabilities of the proposed IEPE method.

4.1. Influence of PPI and PMD on EPP_{norm}

EPP_{min} represents an extreme case with an hour of production while the rest of the process time (8,759 hours) is dedicated to planned maintenance. EPP_{min} for this case is equal to 3.754×10^3. EPP_{max} represents another extreme case with a full production period (for 8,760 hours) and without any planned maintenance state. For this case, EPP_{max} is equal to 6.402×10^3. The normalized *EPP*, EPP_{norm}, is then calculated for various values of parameters. *PPI* and *PMD* practical ranges are considered and both are extended to test the IEPE method.

Figure 5 shows the trend of the EPP_{norm} against *PPI* values. Each curve in Figure 5 is associated with a specific value of *PMD* and it shows that when *PPI* increases EPP_{norm} increases. For curves with shorter *PMD*, the rate of change for EPP_{norm} over *PPI* is smaller. For instance, over the *PPI* range under consideration EPP_{norm} varies very little for *PMD* values below 24 hours. Whereas, when *PMD* corresponds to 120 hours, EPP_{norm} varies substantially.

The rate of change was found to vary for a given *PMD*. When *PPI* is between 1,116 and 1,344 hours, EPP_{norm} almost plateaued for *PMD* between 88 and 104 hours (Figure 5). Two major components of *EPP*, IFu and $\mu(t)$, change throughout the duration of the model time. The variation in $\mu(t)$ defines the next state for the subprocess. The state dictates the value of IFu for the subprocess.

Figure 6 shows the values of EPP_{norm} against *PMD* and demonstrates that higher *PMD* results in lower EPP_{norm} due to the reliability of the subprocess being improved through longer repair states. The other reason for a lower EPP_{norm} with a long *PMD* is that planned maintenance states have lower IFu values as the chemical interactions stop in these states. With a longer *PPI*, the value of *PMD* has a lower impact on EPP_{norm}. For example, over the *PMD* range being considered, when *PPI* is 504 hours EPP_{norm} varies almost three times more than when *PPI* is equal to 1,512 hours. The ratio of operating and non-operating intervals is small when *PPI* corresponds to 1,512. Therefore, the transition to non-operating states of UM and UO with high IFu values result in a high EPP_{norm}. In contrast, the ratio of

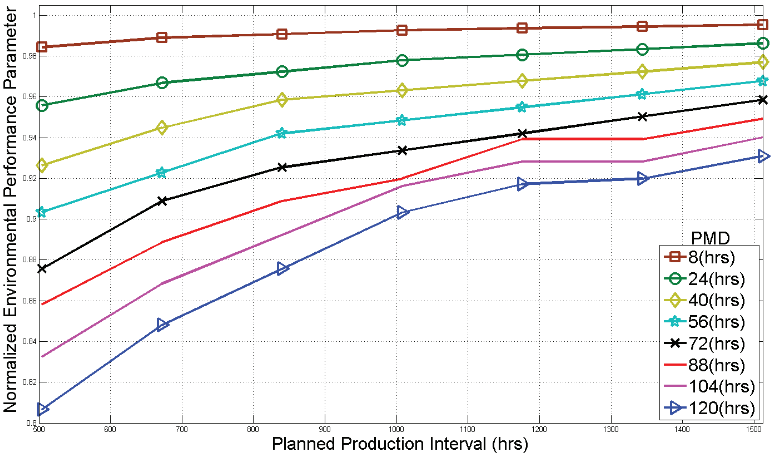

Figure 5: Comparing *EPP* for eight different values of planned maintenance duration between eight hours to five days in two shifts increments.

operating and non-operating intervals is larger when *PPI* is equal to 504 hours. Hence, the operating states are more prevalent when *PPI* is equal to 504 hours, as are the IFu associated with operating states, which result in lower EPP_{norm} values. The various bumps on both Figures 5 and 6 show that the states within the process are changing as are their associated IFu and $\mu(t)$ and this causes changes in the value of the EPP_{norm} and the curves even overlap.

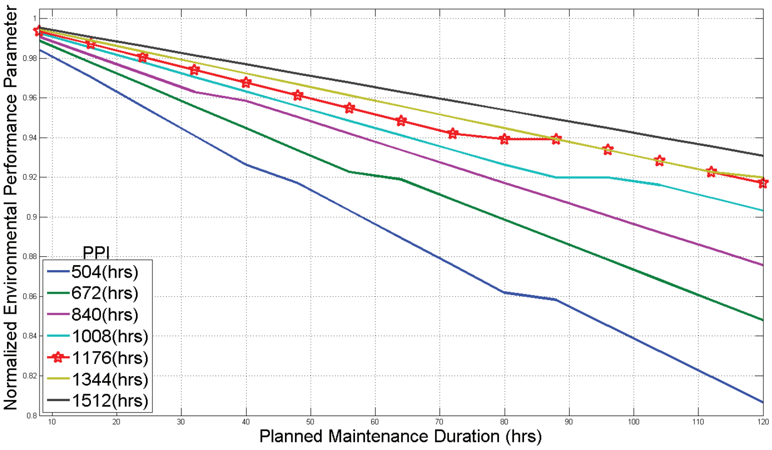

Figure 6: Comparing *EPP* for seven different values of planned maintenance start time between three to nine weeks in one week increments.

Overall, it was observed that a higher *PMD* results in lower EPP_{norm}, i.e. the more time the process spends in the planned maintenance state, the lower the EPP_{norm}. Of course, it is neither feasible nor economically justifiable to spend the whole process time in the planned maintenance state in order to achieve the lowest EPP_{norm}. As such, it is important to acknowledge financial objectives when trying to achieve an improved EPP_{norm}. A suitable number of planned maintenance states and an optimized level of reliability can be used to identify the maximum profit (production output) for an achievable low value of EPP_{norm}. To find these optimized levels, a maintenance policy is required that considers the operational aspects of the process as well as its environmental impacts. In the next section, aleatory uncertainty estimators ($\mu(t)$ and s_t) are monitored to configure a maintenance policy that can accommodate process variations.

4.2. Influence of Failure Rate on Production Period

In this section, the production periods and EPP values are analysed to develop maintenance strategies, including unplanned and planned maintenance. This is done by examining variations in the set of subprocess's failure rates while monitoring the values of aleatory uncertainty estimators, which are the state probability distribution vector, $\mu(t)$, and the state variable, s_t.

Choosing a maintenance policy for an environmentally conscious process will consider both operational aspects and its environmental impacts. Variations within the process associated with operational and environmental issues can be monitored in terms of its aleatory uncertainty parameters. Here, three different sets of failure rates are used to analyse the effect of subprocess failure rates over the aleatory uncertainty outputs, which are the state probability distribution vector ($\mu(t)$) and the state variable (s_t). First, the failure rates of the subprocesses are set to values 10 times lower than the ones presented in Table 3. Second, the failure rates of the subprocesses are equal to those in Table 3. Third, the failure rates are 100 times higher than the ones presented in Table 3. For these three scenarios PMD is set to 8 hours and PPI to 504 hours. The process is examined for a process time of a year (8,760 hours), however the region in which all three different scenarios start to settle is between 500 and 600 hours. Hence, this period is demonstrated in Figures 7 to 9, which is the first period after the first planned maintenance.

Figure 7 shows the results when failure rates are 10 times lower than the ones shown in Table 3. In this scenario, the behaviour of the state probability distribution vector ($\mu(t)$) and the state variable (s_t) settles very quickly, therefore after 8 hours of planned maintenance, the process is operational for all of the time between 512 to 600 hours, as shown in Figure 7 (bottom). This means a constant production between 512 to 600 hours with no interruption.

It could be concerning that the process does not spend most of its operating life in the best operating state, O_1. This is completely related to the initial values chosen for the transition probabilities (the transition coefficients in Equation 9) between operating states and it can be modified to best reflect the real history of the process. The operating period during the whole process time of 8,760 hours is equal to 8,615 hours. This leaves only 145 hours for planned maintenance states. The EPP for this scenario is 6,360.57 as the subprocesses are in operating conditions for the whole process duration. Hence, it might be suitable to alter the maintenance policy accordingly. Instead of the planned maintenance state, a planned inspection state can be introduced with a shorter duration and a higher frequency.

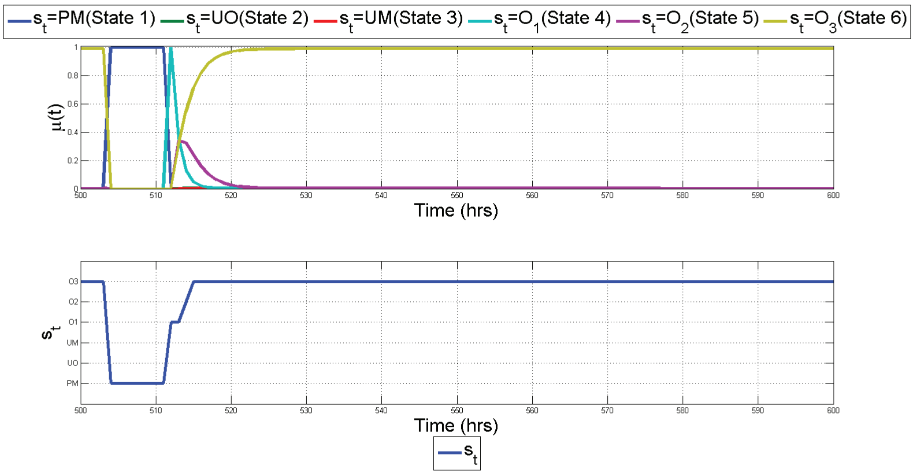

Figure 7: The state probability distribution vector (μ) and state variable of a subprocess between 500 to 600 hours, when the subprocesses' failure rate are 10 times lower than the ones shown in Table 3.

Figure 8 demonstrates the results when failure rates of the subprocesses are equal to those shown in Table 3. The changes in the failure rates influence both the values of the $\mu(t)$ and s_t. When compared to Figure 7, the percentage of visits to state 2, UO, increases from 0% to almost 13%, while the time spent in operating states, O_1, O_2 and O_3, drops from 8,615 hours to 8,215 hours. In Figure 8, $\mu(t)$ for state O_3 is almost equal to 0.5, representing a decrease of 50% when compared to the scenario shown in Figure 7.

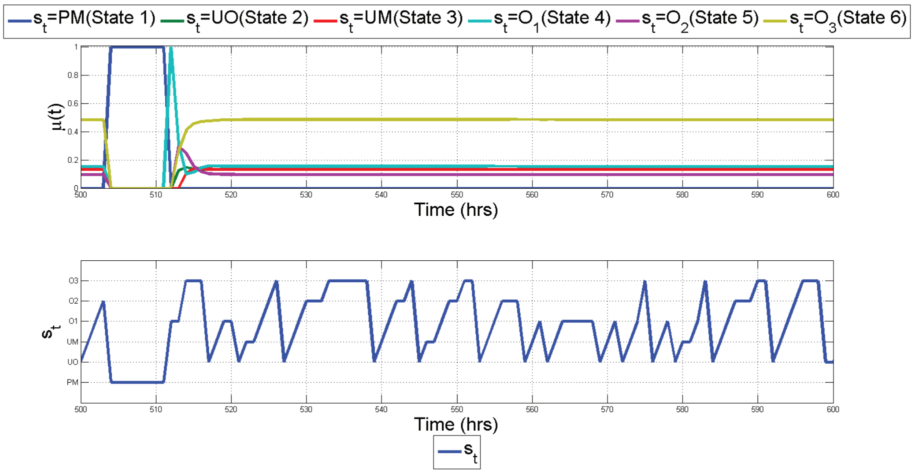

Figure 8: The state probability distribution vector (μ) and state variable of a subprocess between 500 to 600 hours, when the subprocesses' failure rate are equal to the ones shown in Table 3.

The drop in the probability of operating states and the increase in the probability of non-operating states correspond to the variations in the bottom chart in Figure 8. This leads to a drop not only in the production rate but also in the value of IFu and accordingly of EPP. EPP is equal to 6,348.05, which reflects the change in the operating period and consequently the production rate. The non-operating period is almost four times more than the scenario demonstrated in Figure 7, which is a direct result of the increment in the failure rates of the subprocesses. This causes the subprocesses to visit unplanned maintenance and unplanned outage states. These states, despite their low IFu and low contributions to EPP, decrease the production rate that is undesirable specially if it can be prevented with a suitable customized maintenance strategy. The question is if the increment of EPP for less than 0.2% worth the increment of almost 5% in production rate, when comparing this scenario to the scenario demonstrated in Figure 7.

Figure 9 shows the results when failure rates of subprocesses are 10 times more than the ones in Table 3. The rise of the failure rates results in a highly variable values for $\mu(t)$ that only start to converge after 30 hours passed the planned maintenance state. The share of the operating states from 100% in Figure 7 fell to under 28% or 2,474 hours, while the UO period increased to 33% from 13% in Figure 8. Toward 550 hours, $\mu(t)$ values start to converge. For state O_1, $\mu(t)$ converges to 0.27. While for states UO and UM, $\mu(t)$ values are almost equal to 0.4. This means only a third of the time is spent for production and the rest is for maintenance related activities.

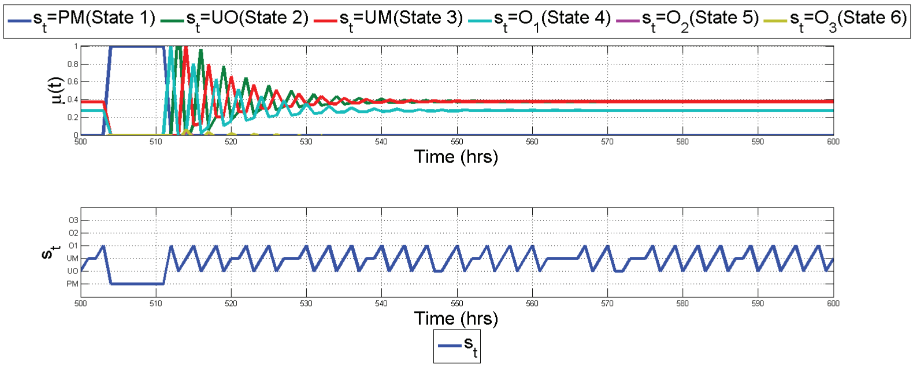

Figure 9: The state probability distribution vector (μ) and state variable of a subprocess between 500 to 600 hours, when the subprocesses' failure rate are 10 times higher than the ones shown in Table 3.

Less time spent in production and more in maintenance result in a lower EPP than the other two scenarios, equal to 6,130.71. However, the fluctuation in the state variable graph demonstrates a highly interrupted production period with less than five hours spent in any of the defined states. The process has a relatively high EPP that is only 3.5% lower than the first scenario's EPP, even though the process is not producing as much as the first scenario. Moreover, it is costing more for various maintenance related tasks. This is an example of an integrated environmental and operational performance, both of which are undesirable for this scenario.

To make decisions for improving the operational and environmental performances of the process, it is important to monitor and analyse highly variable behaviours in the operating and non-operating states. The maintenance strategy of the process can be selected according to these analyses to minimize production loss and environmental impacts at the same time.

Analysis of these three scenarios reveals the influence of failure rates of the subprocesses on $\mu(t)$ and s_t, which have a direct influence on the production rate and on the EPP value of the process. To discuss the relation between the production rate and EPP values in more detail, a set of alternatives are designed to compare the modelling of failure rate on EPP calculation. These alternatives are described in the next subsection.

4.3. Influence of Changes in Failure Rate and Transition Probabilities on EPP

An inclusive holistic model for the evaluation of environmental performance is crucial to decision-making within organisations [Voinov et al., 2014]. If the model does not have the capability to include the reality of a dynamic entity such as an industrial process, the outputs available from the model may not be reliable [Bennett et al., 2013] and as such offer poor guidance for subsequent decision-making. Evaluating the environmental performance of an existing process is useful for decision-making associated with the continual development of the Environmental Management System (EMS) of a company. The model can also be employed to establish new and better processes to complete the same manufacturing requirement. The tradeoffs between environmental and economic objectives are pivotal to the feasibility study of whether or not to invest in a new process. Therefore, the accuracy of the evaluation model results is extremely important.

To demonstrate the modular flexibility of the proposed industrial environmental performance evaluation method in depicting the process, three modelling alternatives are defined for measuring the production rates and EPP. These alternatives are different in modelling the influence of variations in the transition probabilities and the failure rates of subprocesses on EPP calculation. The alternatives use extreme variations in the model's parameters to demonstrate the capability of the model in depicting the process.

4.3.1. Static Modelling Alternative

Static modelling demonstrates a process with fixed failure rates. The duration or start of the planned maintenance state in this alternative does not have an effect on the value of the failure rates. This is modelled by keeping constant the values of transition probabilities and failure rate of subprocesses. The parameters PMD and PPI are set to 56 and 840 hours, respectively. This alternative is representative of a modelling without modular flexibility and therefore no capability in depicting the true reality of an industrial process.

4.3.2. PPI Influence Alternative

PPI Influence alternative tests the influence on EPP of changing the transition probabilities and the failure rates of subprocesses. It changes the transition probabilities between the best operating state and unplanned maintenance as well as the one between unplanned outage and unplanned maintenance.

During the operation period, these probabilities are divided by a factor of 1.005 for every hour of operation, in Figure 10. After the planned maintenance duration, these probabilities are reset to their initial values. A similar approach is followed for the failure rates of subprocesses. The failure rates are multiplied by a factor of 1.005 for every hour of operation. After the planned maintenance duration, the failure rates of subprocesses are reset to their initial values or as-good-as-before. It is noteworthy that all the other transition probabilities in Equation 9 are consequently changed. The parameters of *PMD* and *PPI* are set and equal to 56 and 840 hours, respectively. This alternative represents the aging of subprocesses after hours of operation that increases the chance of random failures and unplanned outages. It depicts a more realistic picture of the process compared to the static modelling.

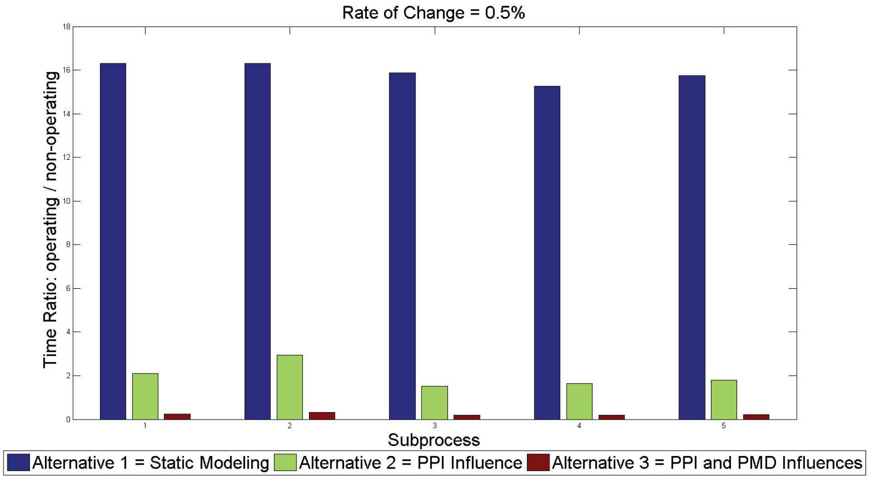

Figure 10: The ratio between the time in the operation and time out of the operation for three alternatives of modelling, when the changes of failure rates, P_{23} and P_{34} probabilities are 1.005.

4.3.3. PPI and PMD Influences Alternative

In the PPI and PMD Influences alternative, the transition probabilities and the failure rates of subprocesses are changed during both operation and planned maintenance durations. In this alternative, the third assumption in Section 2 is relaxed. Instead it is assumed that a subprocess after a planned maintenance can be better with lower failure rate than it had at the start of the process. The change is enforced on transition probabilities between the best operating state and unplanned maintenance as well as the one between unplanned outage and unplanned maintenance. During the operation period, these probabilities are divided by a factor of 1.005 for every hour of operation.

After the planned maintenance duration, these P_{23} and P_{34} probabilities are set to their initial value at the start of the process. If the subprocess has passed a third of its life, the subprocess is replaced with a new one and therefore the transition probabilities are multiplied by a factor of 1.005 for every hour of that planned maintenance state. Similarly, the subprocess' failure rates are multiplied by a factor of 1.005 for every hour of operation. After planned maintenance duration, the failure rates of subprocesses are set to their initial value multiplied by the number of visits to the planned maintenance state to date. This multiplication represents the aging of the subprocess as reflected by how many times it has received a repair. If the process has passed a third of its life, the subprocess is replaced with a new one and therefore the subprocess failure rate is set to its initial value divided by the duration of that planned maintenance state. The parameters of *PMD* and *PPI* are set and equal to 56 and 840 hours, respectively. Similar to the second alternative, all the other transition probabilities in Equation 9 are consequently changed. This alternative depicts as extreme case of the replacement of the near new subprocesses and its effect on the production rate and *EPP*.

4.3.4. Discussing Modelling Alternatives

Figure 10 explores the ratio of operating and non-operating periods when the rate of change is 1.005. The ratio drops dramatically between the first, second and third alternatives. The eightfold difference between the ratio of static modelling and *PPI* Influence shows the importance of using a reality-based model. It is acknowledged that the enforced variations on transition probabilities and failure rates of subprocesses are extreme. This approach magnifies the differences and demonstrates the capability of the flexible evaluation method in modelling what is known in the process and considering what is assumed as unknown or uncertain.

In the second and third alternatives, two types of failures, random failures and aging failures, are considered for the subprocesses. The extreme enforced variations of failure rates might not happen in reality. However, having a model that supports inclusion of such information enhances the confidence of decision-making on the model results. The third alternative takes the modelling further by introducing a replacement of the subprocess at a third of its predicted life. This inclusion of replacement on top of the other two types of maintenance, unplanned and planned, depicts the process in the breakdown period of its life-cycle. For this purpose, the failure rate should be generally based on a Weibull distribution which can be easily implemented in the model.

The *EPP* of these alternatives presents yet another reason for employing an inclusive performance evaluation model (Table 4). The difference between *EPP* are less than 2%. The EPP_{min} is equal for all of the three alternatives. This is according to the definition of EPP_{min}, in which the whole process time for the three alternatives is spent in the planned maintenance state, except the first hour. The values of EPP_{max} however are slightly different for the three cases. This shows that the variations in the failure rates of subprocesses, and consequently the transition probabilities, lead the process to various operating and non-operating states in different alternatives of modelling.

The second and third alternatives have the highest EPP_{max}. This is because the failure rates in these two alternatives are getting higher by every hour of operation. While in the static modelling the failure rate is a fixed value.

When *PMD* is equal to 56 hours and *PPI* to 840 hours, *EPP* of the '*PPI* and *PMD* Influence' is the lowest. This provides a little gain environmentally for a loss of more than a half in the production time.

Table 4: Comparing the influences of changes in failure rates and transition probabilities on EPP when the rate of change variation is 1.005, PMD is equal to 56 hours and PPI is equal to 840 hours; As mentioned in Section 4.1 for EPP_{max} PMD is equal to zero and PPI is equal to process time; For EPP_{min} PMD is equal to process time and PPI is equal to one hours.

Alternative	EPP	EPP_{max}	EPP_{min}	EPP_{norm}
1 (Static)	6,247.8	6,402.7	3,754.3	0.942
2 (*PPI*)	6,146.8	6,413.2	3,754.3	0.900
3 (*PPI* & *PMD*)	6,145.7	6,413.2	3,754.3	0.899

As demonstrated in Subsection 4.2, as the failure rates increase the EPP slightly decreases. However, after maintenance and decrement of the failure rate the highly variable state variables cause an undesired loss of production rate, which is also the case in the third alternative (Figure 10). Therefore, a knowledge about the reality of the process and its environmental performance clarify the choices that should be made in this regard. This decision is based on the process and its associated organisation policies in the Environmental Management System (EMS). The method provides the opportunity to reflect upon such questions for the process owners and accordingly update or review their EMS policies.

5. Conclusion

This paper has proposed an industrial environmental performance evaluation method (IEPE). The proposed IEPE calculates an Environmental Performance Parameter (EPP) for given defined parameters. The EPP identifies the environmental performance of the process and it can be used for policy-making and for the continual improvement of an organisation. This method is presented as a potential tool to resolve the existing need for an integrated industrial environmental performance evaluation technique that provides a clear and inclusive measure to feed the decision-making processes of an organisation. IEPE incorporates the operational aspects of the process including the failure rates of subprocesses and the process maintenance schedule. This approach integrates the environmental and operational performance of the process. Hence, attempts to improve one of these performances lead to changes in the other performance. IEPE considers two sources of data uncertainty, which are termed as epistemic and aleatory uncertainties within the literature.

The existence of epistemic uncertainty is considered within the impact function calculation. This calculation incorporates the potential sources of material release to the environment, referred to as release factors in this paper. Release factors are probability values with epistemic uncertainties. Imprecise probability theory is used to consider their minimum and maximum threshold values. It is assumed that the variation of these probability values, their epistemic uncertainty, is in a minimum and maximum interval. To evaluate if the uncertainty takes the probability value higher than maximum or lower than minimum threshold, a sensitivity analysis can be used, which has not been included in this paper. Sensitivity analysis can capture the level of epistemic uncertainty for a given release factor. The result of this sensitivity analysis can readily be employed by the IEPE model as a future study. This is possible when the current release factors and standard and target values are replaced by the results of the sensitivity analysis. There is also epistemic uncertainty associated with the values of data incorporated into the model, which can be treated in a similar fashion. This paper has not discussed this type of uncertainty due to data limitations.

The aleatory uncertainty about the process and possibility of transition between operating and non-operating states are treated via a proposed multistate transition matrix. The transition matrix uses a function of the subprocesses' failure rates to define its transition probabilities. A state probability transition vector is then calculated based on this transition matrix that follows the memoryless property of Markov chains. This vector gives the probability of each operating or non-operating state at every time step and hence encapsulates the respective aleatory uncertainty.

Consideration of these uncertainties brings clarity to policy-makings of the process and ensures a continual improvement of an organisation. The result of the proposed IEPE is easy to use as a unitless number, called the Environmental Performance Parameter (EPP). EPP is readily calculated when the adequate data is available as is the case for other performance evaluation models. EPP can be normalized according to its minimum and maximum values for comparing various processes within one organisation or between several organisations.

The proposed model is sufficiently flexible to accommodate the need of the user for evaluating a particular organisation's environmental performances. The model could be improved by an addition of economic performance evaluation. This economic evaluation is proposed as the next part of this research study. This addition will potentially allow the EPP to be connected with operating costs and the associated return on assets to enable a more holistic performance appraisal. In order to achieve a desired and economically viable EPP, a multi-objective optimization approach is proposed as the next part of this study.

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APPENDIX A- Generality of IFu Calculation

The proof of generality of IFu calculation in any condition: Let $\frac{S_{Y_i}}{Y_i} = \Psi_i$, if $n_1 = ... = n_i = ... = n_N$ then $W_i = \frac{1-\Psi_i}{n_i}$ and ω_i can be written as:

$$\omega_i = \frac{(1-\Psi_i)}{N-(\Psi_1+\Psi_2+...+\Psi_N)} \tag{A-1}$$

The denominator of Equation A-1 would be zero when $(\Psi_1+\Psi_2+...+\Psi_N) = N$ resulting in an infinite IFu. However, it can be reasoned that the denominator cannot be zero as follows: Every organisation's goal is to reduce Y_i to the target level or S_{Y_i}. If Y_i is less than the target, it is assumed that the IFu calculation is not required, as the goal is already achieved. Thus, $Y_i > S_{Y_i}$, $\forall i = 1,2,...,N$. $Y_i > S_{Y_i}$ leads to $\Psi_i < 1$ and $(\Psi_1+\Psi_2+...+\Psi_N) < N$.

If $n_1 \neq ... \neq n_i \neq ... \neq n_N$, Equation A-1 becomes:

$$\omega_i = \frac{(1-\Psi_i)/n_i}{(1/n_1+1/n_2+...+1/n_N)-(\Psi_1/n_1+\Psi_2/n_2+...+\Psi_N/n_N)} \tag{A-2}$$

Since $\Psi_i < 1$ and $n_i > 0$, we have $\Psi_i/n_i < 1/n_i$ and consequently:

$$\frac{1-\Psi_i}{n_i} > 0 \tag{A-3}$$

So Equation A-2 is replaced with:

$$\omega_i = \frac{(1-\Psi_i)/n_i}{(1/n_1-\Psi_1/n_1)+(1/n_2-\Psi_2/n_2)+...+(1/n_N-\Psi_N/n_N)} \tag{A-4}$$

The denominator is always greater than zero in Equation A-3. Thus, ω_i, in Equation A-4, is always positive finite. Therefore, the denominator cannot be zero for all $\frac{S_{Y_i}}{Y_i} < 1$, and $Y_i > S_{Y_i}$ should satisfy the use of the IFu calculation.

APPENDIX B- Proposed Transition Matrix Elements

λ is the failure rate of the subprocess and also shows the degradation of the subprocess that cause the transition from higher operating states to the lower ones. $\lambda_3 > \lambda_2 > \lambda_1$ and $\alpha_3 > \alpha_2 > \alpha_1$, while $\beta_1 > \beta_2 > \beta_3$ and $\gamma_1 > \gamma_2$.

The other elements of the transition matrix are as follow:

The elements of the fourth row of the matrix demonstrate that the transition to the second, fourth, fifth and sixth states are possible from the fourth state.

$$P_{42} = P(UO|O_1) = \alpha_1 \times \lambda = \lambda_1 \tag{B-1}$$

$$P_{44} = P(O_1|O_1) = \beta_1 \times (1 - \alpha_1 \times \lambda) = (1 - \lambda_1)\beta_1 \tag{B-2}$$

$$P_{45} = P(O_2|O_1) = \beta_2 \times (1 - \alpha_1 \times \lambda) = (1 - \lambda_1)\beta_2 \tag{B-3}$$

$$P_{46} = P(O_3|O_1) = \beta_3 \times (1 - \alpha_1 \times \lambda) = (1 - \lambda_1)\beta_3 \tag{B-4}$$

The elements of the fifth row of the matrix demonstrate that the transition to the second, fifth and sixth states are possible from the fifth state and are calculated as shown by Equations B-5-B-7.

$$P_{52} = P(UO|O_2) = \alpha_2 \times \lambda = \lambda_2 \tag{B-5}$$

$$P_{55} = P(O_2|O_2) = 0 \tag{B-6}$$

$$P_{56} = P(O_3|O_2) = \gamma_1 \times (1 - \alpha_2 \times \lambda) = (1 - \lambda_2)\gamma_1 \tag{B-7}$$

Finally the elements of the sixth row of the matrix demonstrate that the transition to the second and sixth states are possible from the sixth state and can be calculated given the Equations B-8 and B-9.

$$P_{62} = P(UO|O_3) = \alpha_3 \times \lambda = \lambda_3 \tag{B-8}$$

$$P_{66} = P(O_3|O_3) = \gamma_2 \times (1 - \alpha_2 \times \lambda) = (1 - \lambda_2)\gamma_2 \tag{B-9}$$

After every unplanned maintenance, it is assumed that the subprocess is As-Good-As-Before (AGAB) and therefore reliable enough to transit to the fourth state (Equation B-10).

$$P_{34} = P(O_1|UM) = 1 - \alpha_2 \times \lambda = 1 - \lambda_3 \tag{B-10}$$

The transition to the planned maintenance state from the fourth, fifth and sixth states are time dependent and does not happen when it is not time for planned maintenance, therefore as demonstrated in Equation B-11it is zero equal to their transition to unplanned maintenance.

$$P_{41} = P_{51} = P_{61} = P(PM|O_1, O_2, O_3) = P(UM|O_1, O_2, O_3) = 0 \tag{B-11}$$

APPENDIX C- Transition Matrices for subprocesses

For the initial transition matrix of a subprocess the transition coefficients are chosen in a way that following are true. It is important to note that as the time progress the transition matrix may change depending on the failure rate distribution function and if it has a fixed value or a dynamic one.

α_i and β_i, $i = 1,2,3$ and γ_j, $j = 1,2$ are transition coefficients given $\alpha_3 + \alpha_2 + \alpha_1 = 1$, $\beta_1 + \beta_2 + \beta_3 = 1$ and $\gamma_1 + \gamma_2 = 1$. Moreover, α_i and β_i are chosen in a way that $\alpha_3 > \alpha_2 > \alpha_1$. Therefore, $\lambda_3 > \lambda_2 > \lambda_1$. While $\beta_1 > \beta_2 > \beta_3$ and $\gamma_1 > \gamma_2$.

- the value of probability transition for failing from O_1 and transiting to UO is the lowest when compared to the same transition from O_2 to UO and respectively from O_3 to UO. In other terms, $\lambda_1 < \lambda_2 < \lambda_3$.
- the value of probability transition for failing from O_1 and moving to O_2 is higher than moving to O_3. In other terms, $\beta_3(1-\lambda_1) < \beta_2(1-\lambda_1)$.
- staying in O_1 is more probable than transiting to O_2 ($\beta_2(1-\lambda_1) < \beta_1(1-\lambda_1)$).
- failing while in O_2 and therefore moving to UO is less probable than staying in O_2 ($\lambda_2 < (1-\lambda_2)\gamma_1$).
- moving to O_3 from O_2 is less probable than staying in O_3 but more probable than failure of O_2 ($\lambda_2 < (1-\lambda_2)\gamma_2 < 1-\lambda_3$).
- staying in O_3 is more probable than failing to UO ($\lambda_3 < 1-\lambda_3$).
- staying in O_3 is more probable than failing when in O_1 and transiting to UO ($\lambda_1 < 1-\lambda_3$).
- staying in O_1 is less probable than staying in O_3 ($\beta_1(1-\lambda_1) < 1-\lambda_3$).

$$\prod_{Reactor} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0.2 & 0.8 & 0 & 0 \\ 0 & 0.00155\alpha_1 & 0 & \beta_1(1-0.00155\alpha_1) & \beta_2(1-0.00155\alpha_1) & \beta_3(1-0.00155\alpha_1) \\ 0 & 0.00155\alpha_2 & 0 & 0 & \gamma_1(1-0.00155\alpha_2) & \gamma_2(1-0.00155\alpha_2) \\ 0 & 0.00155\alpha_3 & 0 & 0 & 0 & 1-0.00155\alpha_3 \end{bmatrix} \tag{C-1}$$

Due to the important role of the reactor, it is assumed that the repair is a more time consuming task and therefore probability of staying in UM is higher than zero.

$$\prod\nolimits_{HeatExchanger} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0.00456\alpha_1 & 0 & \beta_1(1-0.00456\alpha_1) & \beta_2(1-0.00456\alpha_1) & \beta_3(1-0.00456\alpha_1) \\ 0 & 0.00456\alpha_2 & 0 & 0 & \gamma_1(1-0.00456\alpha_2) & \gamma_2(1-0.00456\alpha_2) \\ 0 & 0.00456\alpha_3 & 0 & 0 & 0 & 1-0.00456\alpha_3 \end{bmatrix} \tag{C-2}$$

$$\prod\nolimits_{Absorber} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0.2 & 0.8 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0.00524\alpha_1 & 0 & \beta_1(1-0.00524\alpha_1) & \beta_2(1-0.00524\alpha_1) & \beta_3(1-0.00524\alpha_1) \\ 0 & 0.00524\alpha_2 & 0 & 0 & \gamma_1(1-0.00524\alpha_2) & \gamma_2(1-0.00524\alpha_2) \\ 0 & 0.00524\alpha_3 & 0 & 0 & 0 & 1-0.00524\alpha_3 \end{bmatrix} \tag{C-3}$$

The required paper work or obtaining the necessary equipment for the maintenance can take some time and therefore the probability of staying in UO is more than zero for absorber.

$$\prod\nolimits_{Converter} = \begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0.2 & 0.8 & 0 & 0 \\ 0 & 0.00365\alpha_1 & 0 & \beta_1(1-0.00365\alpha_1) & \beta_2(1-0.00365\alpha_1) & \beta_3(1-0.00365\alpha_1) \\ 0 & 0.00365\alpha_2 & 0 & 0 & \gamma_1(1-0.00365\alpha_2) & \gamma_2(1-0.00365\alpha_2) \\ 0 & 0.00365\alpha_3 & 0 & 0 & 0 & 1-0.00365\alpha_3 \end{bmatrix} \tag{C-4}$$

APPENDIX D- Methodology Algorithms for Reproducibility Purposes

Algorithm 1: EPE method algorithm - Initialization.

```
Choose a process;
Choose a design;
Divide the process into subprocesses;
Identify the number of subprocesses;
Identify the number of material in each subprocess;
Initialize the material parameters;
Initialize the subprocess parameters;
Initialize the process time;
Initialize the PM duration ($PMD$);
Initialize the Planned Production Interval($PPI$);
```

Algorithm 2: EPE method algorithm - IFu Calculation.

```
while number of subprocesses $\neq 0$ do
    Set $\prod$;
    Set $\mu(t=0) = [0\ 0\ 0\ 1\ 0\ 0]$]);
    Set $\mu(t=\iota M) = [1\ 0\ 0\ 0\ 0\ 0]$;
    for $t = 1$ : process time do
        Calculate $\prod$ (using Equation 9);
        Calculate $\mu(t)$ (Section 2.4);
    for $i = 1$ : number of the material (using Table 2) do
        for $s_t = 1$ : number of states (using Table 1) do
            case impact is
                Toxicity : $X_{1u,i}$;
                Photochemical smog : $X_{2u,i}$;
                Acid deposition : $X_{3u,i}$;
                Global warming : $X_{4u,i}$;
                Ozone depletion : $X_{5u,i}$;
                Heavy metal : $X_{6u,i}$;
                NOx : $X_{7u,i}$;
                Pesticide : $X_{8u,i}$;
                Fertilizer : $X_{9u,i}$;
                Water : $X_{10u,i}$;
                Physical material : $X_{11u,i}$;
                Chemical material : $X_{12u,i}$;
                Natural gas : $X_{13u,i}$;
                Oil : $X_{14u,i}$;
                Coal : $X_{15u,i}$;
            while $X_{u,i} \neq 0$ do
                $W_{i1} = (Y_1 - S_{y1})/(n_1 \times Y_1)$;
                $W_{i2} = (Y_2 - S_{y2})/(n_2 \times Y_2)$;
                $W_{i3} = (Y_3 - S_{y3})/(n_3 \times Y_3)$;
                $W_{i4} = (Y_4 - S_{y4})/(n_4 \times Y_4)$;
                $W_{i5} = (Y_5 - S_{y5})/(n_5 \times Y_5)$;
                if $X_{u,i}$ is for an output then
                    $W_{i6} = (X_{u,i} - S_{X_i})/(n_i \times X_{u,i})$;
                else
                    $W_{i6} = 0$;
            if $W_i > 0$ then
                $\omega_i = W_i / \sum_i W_i$;
            else
                $\omega_i = 0$;
    $X_i = X_{u,i}/S_{X_i}$;
    Calculate $IFu_u = \sum_i \omega_i \times X_i$;
```

Algorithm 3: EPE method algorithm - State Probability Distribution Vector Calculation.

```
Set $\prod$;
if $t \geq PPI$ and $t < PPI + PMD$ then
    $\prod = [ones(6,1)\ zeros(6,5)]$;
    if $t = PPI + PMD$ then
        t=0;
$\mu_u(t) = \mu_u(t-1) \times \prod$;
```

Algorithm 4: EPE method algorithm - EPP Calculation.

```
for $PMD = 8 : 8 : 120$ do
    for $PPI = 504 : 168 : 1512$ do
        for $t = 2 :$ process time do
            Calculate $EPP_u(t) = \sum_t (\sum_u (\mu_u(t) \times IFu_u))$;
```