

Industrial Environmental Performance Evaluation - Comparison and Sensitivity Analysis

S. Shokravi , A.J.R. Smith, C.R. Burvill and S. Maheswararajah

*Department of Mechanical Engineering, School of Engineering, University of
Melbourne, Australia
s.shokravi@student.unimelb.edu.au*

Abstract: Environmental Performance Evaluation (EPE) methods provide an objective numerical measurement for understanding the environmental impact of industrial activities. Currently available methods have the following drawbacks: first, most of them do not provide a single measure, this results in multiple incomplete and inaccurate measures that are not compatibly interpretable. Second, they only consider a limited number of environmental impacts for subsequent evaluation. Third, they ignore the uncertainties involved in the industrial process; e.g. random data or incomplete data collection. In this paper, a new method is used to compare three different designs of formaldehyde production process. These designs share a few common elements. This paper investigates through sensitivity analysis how changes in the calculated Environmental Performance Parameter (EPP) can be attributed to differences in the design and/or operational parameters of the equipment. The results of this study reveal the influence of employing different designs or unit operations on the calculated EPP. A process manager can use these results to determine the differing costs associated with alternate modifications to achieve best value. Moreover, this approach can show whether the different sources of uncertainty in the input of an EPE contribute to those in the output (EPP), such as possible human errors or lack of information about process and environment interactions.

Keywords: Environmental Performance; Sensitivity Analysis; Uncertainty; Reliability.

1 INTRODUCTION

Industrial processes convert raw materials into finished goods and involve chemical and mechanical steps for manufacturing item(s). Unlike batch operations, industrial processes are carried out in large scale. Therefore, they change an otherwise rare material into a commodity. However, large scale industrial processes not only result in desired end products, but also in undesired by-products, many of which are toxic, hazardous to humans and the environment.

Environmental performance of an industrial process is the result of the management of its environmental aspects. These aspects are the interaction of the process products or activities with the environment. Environmental Performance Evaluation (EPE) methods are employed to provide the management with reliable information on whether the environmental performance of an organization is acceptable or not. The indexes, provided by EPE methods in the literature, partially reveal the harmful effects of processes and how to decrease these effects by altering the design [Palaniappan, 2004; Cave and Edwards, 1997]. The majority of these indexes are based on scoring, benchmarking and ranking approaches, specifically in the chemical industry and the dominant use of Inherent Safer Design (ISD) approaches [Edwards, 1993]. Some ranking and scoring methods are not

accurate due to the biased expert opinion and hence have the uncertainty associated with expert judgment [Jia et al., 2004].

Moreover, the lack of an inclusive hazard evaluation and uncertainty appraisal in conventional environmental performance indexes lead to some shortcomings, such as incomplete hazard assessments and unreliable results. Ranking based EPE methods are all capable of comparison between processes based on their environmental hazard, but the question is how complete and rigorous these comparisons are. If comparisons are based on incomplete and inaccurate methodologies, the result cannot be fully trusted. An EPE method proposed by Shokravi et al. [2012] provides an Environmental Performance Parameter (*EPP*) that encapsulates the harmful impacts of an industrial process on the environment and how operation and maintenance policies can decrease such impacts. Therefore, in this paper a comparison is presented based on this methodology which encapsulates industrial process, operational and non-operational activities and the possibility of their hazardous events.

The aim of this paper is to employ the proposed environmental performance evaluation method by Shokravi et al. [2012] and find the parameters that have the biggest influence on its result. This helps the method's users to find the most influential way for improving the processes' aspects and hence decreasing their adverse environmental impacts. Moreover, the lack of clarity in some of these index assessments and the need for specialized data limit the method's implementation and credibility. Therefore, the comparison in this paper is based on the new methodology which is associated with the design as well as unit operation characteristics and maintenance strategies.

The remainder of this paper is as follows: Section 2 introduces the employed EPE methodology on which the sensitivity analysis of this paper is based. Section 3 presents the sensitivity analysis for the EPE methodology, discusses the parameters that are influential on EPE results, and implements the analysis on three different designs of formaldehyde production. The results are presented and discussed in Section 4. Section 5 concludes the paper by highlighting the contributions and avenues for further research.

2 ENVIRONMENTAL PERFORMANCE EVALUATION METHOD

The EPE method [Shokravi et al., 2012] employs a Markov generated model. The method makes the following assumptions:

- A given industrial process has fixed process time, number of operating units, inputs and outputs. An operating unit in the process has inputs, outputs and a task to do. In this paper, the task is chemical interaction. The combination of a unit operation, its inputs, outputs and task is called a subprocess. Every input and output has an environmental impact. The impact is calculated for every unit operation and every state.
- The process time is divided into operational and non-operational intervals. Each interval includes a number of states. Operational intervals include different levels of operating states based on the reliability and availability of the unit operation. Such operating states are O_1 , O_2 and O_3 . Non-operating intervals include Planned Maintenance (*PM*), Unplanned Maintenance (*UM*) and Unplanned Outage (*UO*) states.
- Each subprocess begins in the operating state of O_1 . After a visit to *PM* state the unit operation always transits to the operating state of O_1 . This means that the repair is perfect and always restores the component to as-good-as-new. The

transition to *PM* state is time based and happens at every M time steps. Planned maintenance duration is equal to Δ , where $\Delta \ll M$.

- No unit operation can work indefinitely without faults, therefore $\lim_{t \rightarrow \infty} R(t) = 0$, where, $R(t)$ is the reliability of a unit operation at time t . $R(t)$ is a non-increasing, continuous, monotonic function with values ranging between 0 and 1 in the time interval of $[0, \infty)$ [Sahner et al., 1953].

This method provides a single number to show the adverse impacts of an industrial process on the environment. A single index is readily understood by non-expert personnel and, when compared to other environmental performance assessment methods, is not computationally intensive. This single index meets the explicit corporate preference for a procedure that results in a simple measurement and has the ability to engage all levels of employee with associated environmental performance assessment programs and schemes. Aggregation of ranking based indexes into a single index is not possible as it will result in multiple indexes for different aspects of the process that are not interpretable in a compatible manner.

This method is based on a Markov generated model that considers transition probabilities of the model dependent on time and the reliability of the system. Therefore, the transition probabilities are estimated dynamically. It models the operating and non-operating periods of the process as different Markov states to acknowledge the inherent uncertainty in the industrial operations. Moreover, the calculation of Potential Impact Hazard (*PIH*) is based on environmental impact calculation and the weighting that captures the likelihood of the hazard occurrence in each Markov state. The impacts are calculated based on equations such as those in Table 1 and the weightings are calculated by the standard level of chemical release to the environment according to the EPA guidelines [Environment Protection Agency, 2001, 2004, 1998] and their actual occurrence. The *EPP* is the expected value of the calculated *PIH* over the defined Markov states. The states are incorporated in the *EPP* calculation by the state distribution vector, $\mu(t)$, that shows the spent time and the probability of being in each Markov state. The model also has the ability to link the outputs to the maintenance policy of the process in order to distinguish between various improvement opportunities. This method estimates the *EPP* for different planned maintenance- equipment replacement- durations and start times to show the effect of maintenance policy on the *EPP*. The employed EPE method has five steps: 1. Initializing the process information. 2. Calculating the environmental impact of each subprocess. 3. Calculating the Markov transition matrix for each subprocess. 4. Calculating the state distribution vector of each subprocess. 5. Calculating the *EPP* for the whole process.

Environmental Impact Calculation: A new Potential Impact Hazard (*PIH*) calculation for associated environmental impacts has been introduced by Shokravi et al. [2012]. It calculates a weighing for each impact in every state, diminishing the need for ranking and scoring used by other methods in the literature. Standard levels (St_i) based on guidelines [Environment Protection Agency, 2001, 2004, 1998] are used for the chemical exposure in the environment. *PIH*—a vector value—is calculated by $PIH_c = \sum_{i=1}^N \omega_i \times X_i$, where ω_i is the weighting for each impact and X_i is the impact value calculated from functions demonstrated in Table 1. X_i s are dimensionless by dividing each over the standard level of chemical exposure based on [Environment Protection Agency, 2001, 2004, 1998] (X_i/St_i). To calculate ω_i the distance between the current chemical exposure and the one based on the organization target is considered.

Markov Transition Matrix: The Markov transition matrix ($\Pi_c(t)$) is calculated for six different states: Planned Maintenance (*PM*), Unplanned Maintenance (*UM*), Unplanned Outage (*UO*), Operation 1 (*O1*), Operation 2 (*O2*), Operation 3 (*O3*). Every element of

Table 1. Employed equations for the PIH calculation [Hatakeyama et al., 1991; Verschueren, 1996; Hatakeyama et al., 1991].

Impacts	Sub-impacts	Equation	
Air pollution	Toxicity	$X_1 = K_1 + K_2 \times Ln(LC_x)$	
	Photochemical	$X_2 = (0.75/6) \times [Prop - Equiv](\text{ozone ppb})$	
	Smog	$[Prop - Equiv] = PEC \times \frac{k_{OH}}{k_{OH}(C_3 H_6)}$	
	Acid	$X_3 = \frac{PEC}{CL}$	
	Deposition		$r_m = \frac{1}{(H \times 3000) + 100f_0}$
			$CL = 1624.7r_m - 9.04$
	Global Warming	$X_4 = (Warming) \times Q(\text{years } cm^{-2} atm^{-1})$	
		$(Warming)_i = \frac{\tau \times IR_{abs}}{MM_i}$	
	Ozone Depletion	$X_5 = OD \times \frac{Q}{MM}$	
		$OD = \tau \times (n_{Cl} + 30n_{Br})(\text{years molecule}^{-1})$	
	Water Pollution	Heavy Metals	$X_6 = \text{Quantity of the metal}$
	Soil Pollution	NO_x	$X_7 = \text{Quantity of the Emitted } NO_x$
		Pesticides	$X_8 = \text{Quantity of the used Pesticides}$
		Fertilizers	$X_9 = \text{Quantity of the used Fertilizers}$
	Resource Depletion	Water	$X_{10} = \text{Quantity of the used Water}$
	Physical Material	$X_{11} = \text{Quantity of the used material}$	
	Chemical Material	$X_{12} = \text{Quantity of the used chemical}$	
	Natural Gas	$X_{13} = \text{Quantity of the used natural gas}$	
	Oil	$X_{14} = \text{Quantity of the used oil}$	
	Coal	$X_{15} = \text{Quantity of the used coal}$	

this matrix is associated with the reliability and availability of the subprocess. If the subprocess is available and reliable, it can be in the operational states, otherwise a transition to PM or UM is necessary to revive the machine. An unexpected degradation in machine reliability causes a transition to UO state. From this state, the only transitions allowable are to UM or PM (For more detail about the proposed transition matrix by Shokravi et al. [2012] please contact the corresponding author).

State Distribution Vector Calculation: The EPP calculation is based on PIH_c and the state distribution vector ($\mu_c(t)$) which is the vector dependent on the Markov transition matrix from Step 3 and also based on Markov assumption ([Shokravi et al., 2012]). Markov assumption indicates that the values in any state are only influenced by the values of the state that directly preceded it. Hence, $\mu_c(t = n) = \mu_c(t = 0) \times \prod_c(t = 1) \times \dots \times \prod_c(t = n)$ where, t is the process time, c is the cycle of operation including different states and n is the final time, given the methodology assumption that each subprocess starts with the operational state of O_1 , $\mu_c(0) = [0 \ 0 \ 0 \ 1 \ 0 \ 0]$.

EPP Calculation: EPP is the expected overall environmental hazard from the process as a whole allowing for each subprocess to be in each of the recognized states and is equal to $EPP = \sum_{t=1}^n (\sum_{u=1}^{n_u} (\mu_u(t) \times PIH_u^T))$, where n is the total process time and n_u is the number of operating units.

3 SENSITIVITY ANALYSIS

A three-stage experiment is conducted to provide the Sensitivity Analysis (SA) with information. In Stage 1, SA for design variations is studied. To provide a base for comparison, common operational parameters are applied to three distinct designs used to complete a common process, and their $EPPs$ are compared. The Sensitivity Index (SI) of EPP over the design (D) is calculated as $(SI_{EPP-D} = \frac{\Delta EPP/EPP_0}{\Delta D/D_0})$. In Stage 2, by enhancing their reliability parameter, designs are improved. These improved designs are compared with their original versions to carry out SA for the Reliability (R) parameter as demonstrated by $(SI_{EPP-R} = \frac{\Delta EPP/EPP_0}{\Delta R/R_0})$. In Stage 3, SA for the combination of reliability and

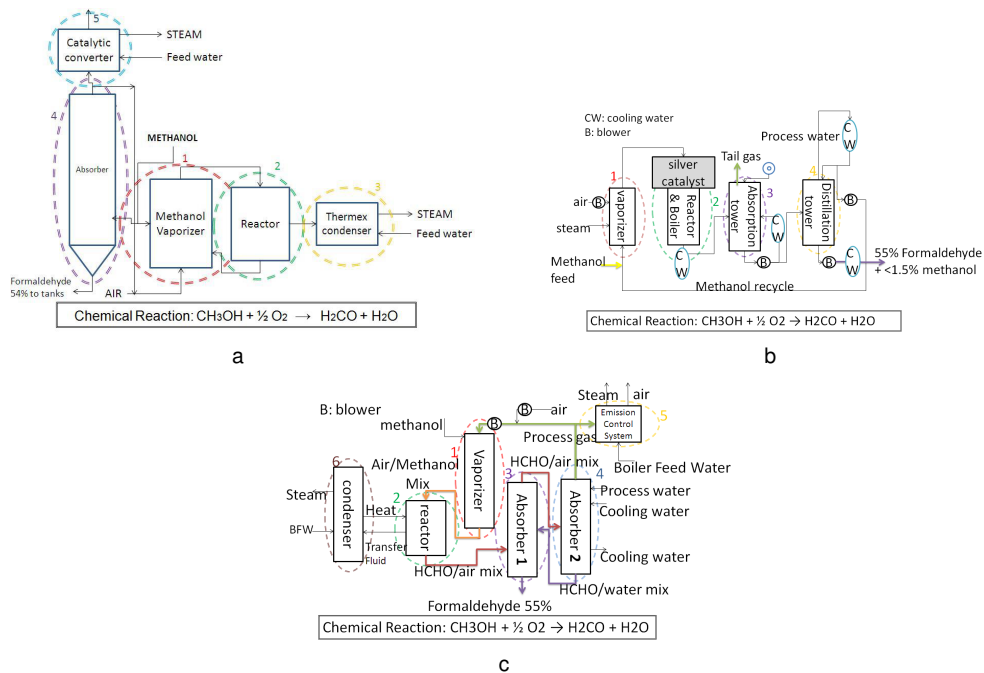


Figure 1. Schematic of the three designs for formaldehyde production process: a. Basic process [Mead, 2007], b. Design with the distillation tower and silver catalyst [Kirk and Othmer, 1991-1998, p. 495, v. 11], c. Methanol oxidative dehydrogenation process with two absorbers.

design parameters is conducted as shown by $(SI_{EPP-D\&R} = \frac{\Delta EPP/EPP_0}{(\Delta D/D_0)(\Delta R/R_0)})$. Where D_0 , EPP_0 and R_0 are the base values for each variable. There are three different designs for formaldehyde production shown in Figures 1a, 1b and 1c. They have 5, 4 and 6 unit operations respectively, with similar tasks, inputs and outputs. The aim is to investigate whether the parameter variations, including the design, unit operation or their combination, can affect the calculated EPP .

The three-stage experiment provides the information necessary to analyze the sensitivity of EPE output to EPE inputs. Here two dominant inputs of the EPE method are chosen: design and unit operation reliability. Design is considered a dominant input as the focus of many previous studies is environmental safety improvement by finding an inherent safer design [Palaniappan, 2004; Gunasekera and Edwards, 2006; Etowa, 2002]. The unit operation reliability parameter is one of the focus points of the employed EPE method [Shokravi et al., 2012].

The first design to be analyzed, shown in Figure 1a, includes five unit operations noted as 1-5 in the schematic: a vaporizer, reactor, thermex condenser, absorber and catalytic converter, respectively. This is the base design for SA in this paper and the design that others are compared to. The second design, Figure 1b, only encompasses four unit operations. It uses a distillation tower instead of a thermex condenser and a catalytic converter. Finally, the last design, shown in Figure 1c, has two absorbers instead of the one in the base design.

The first stage of the simulation determines the most environment-friendly design out of the three. The second stage examines the importance of maintenance on improving the unit operation reliabilities and consequently the EPP . Finally, the third stage investigates the level of improvement in EPP considering enhancements in both design and unit operation reliability. Each industrial process owner should evaluate their EPP and

Table 2. The assumed values for unit operation failure rates.

The hidden factor/unit operation	Data	Value
human error	failure rate	39.6E-3
spills and leakage	failure rate	67.6E-3
gas detection system	failure rate	26.3E-3
low-temperature detector	failure rate	11.4E-3
high-temperature detector	failure rate	11.8E-3
Catalyst Converter	failure rate	3.65E-3
	repair rate	89.9E-3
Distillation Tower	failure rate	1.65E-3
	repair rate	0.899E-3
Absorber1, 2	failure rate	5.24E-3
	repair rate	79.8E-3
Reactor	failure rate	1.55E-3
	repair rate	99.9E-3
Vaporizer	failure rate	2.55E-3
	repair rate	0.833
Condenser	failure rate	1.56E-3
	repair rate	0.487

define a threshold they want to reach. This provides a clear idea about which stage of the simulation gives the level of *EPP* improvement that they are looking for, and what variation (in reliability, design or both) should take place. Table 2 presents the reliability data used for this simulation which are assumed values based on expert opinions.

It is noteworthy to mention some points regarding the calculation of SI_{EPP-D} : SI is estimated through calculating the variation of *EPP* over its base value over the calculation of design over its base value. Since design is not a measurable component but more of a qualitative parameter, it is not able to directly meet the need for SI calculation. However, other variables can be used as surrogates for design, e.g. the number of unit operations or the dollar value of the unit operation or cost of changing designs. In the case of this paper, design is treated as being directly proportional to the number of unit operations (n_u). However, as the sign of SI represents whether there has been an improvement of *EPP* it is necessary to use the modulus of $\Delta n_u/u_0$. Therefore, SI_{EPP-D} and $SI_{EPP-D\&R}$ are replaced by equations in (1):

$$SI_{EPP-n_u} = \frac{\Delta EPP/EPP_0}{|\Delta n_u/u_0|} \quad \text{and} \quad SI_{EPP-n_u\&R} = \frac{\Delta EPP/EPP_0}{(|\Delta n_u/u_0|)(\Delta R/R_0)} \quad (1)$$

For this paper the Reliability of equipment is calculated by $R = \exp(-\lambda t)$, where λ is the equipment failure rate. Process reliability is calculated by $R = \prod_{u=1}^{n_u} (R_n)$ for serial configuration of equipment and by $R = 1 - \prod_{u=1}^{n_u} (1 - R_n)$ for parallel configuration [AS IEC 61078, 2008].

4 RESULTS

Decreasing the number of unit operations from five in the first design to four, in the second design, improves the *EPP* by 12% ($EPP_{n_u=5} = 5.58E+6$ and $EPP_{n_u=4} = 4.90E+6$). Increasing the number of unit operations from five in the base design to six in the third design, however, increases the *EPP* by about 19% ($EPP_{n_u=6} = 6.63E+6$). These variations show the impact of the design on the *EPP* calculation, even though only the num-

Table 3. *EPP* Sensitivity Indices over the reliability of the process design and the number of unit operations in the design (R' is the improved reliability for a given design).

Base Design	Alternative Configurations					
	$n_u=5$	$n_u=4$	$n_u=6$	$(R', n_u=5)$	$(R', n_u=4)$	$(R', n_u=6)$
$n_u=5$	-	-0.603	0.950	-1.043	-119.636	254.663
$n_u=4$	-	-	-	-	-1.187	-
$n_u=6$	-	-	-	-	-	-0.877

ber of unit operations is considered in *SI*. The fact that input and output of the distillation tower are different from those of the catalytic converter and thermex condenser is also an influential factor on the *EPP*. This shows the influence of the chemical material as well as the fact that the input of the condenser is only water while the inputs and outputs of the absorber are toxic and corrosive materials with adverse environmental impacts. The *EPP* sensitivity to the number of unit operations is between -0.603 to 0.950 for SI_{5-4} and SI_{6-5} (Table 3).

In Stage 2, a pool of data was created for comparing each design with an improved version of itself. For this purpose, Table 2 data are used to calculate the original reliability of the process. Then the failure rate of the each unit operation is improved in turn by two degrees of magnitude, to find the one with the greatest effect on the *EPP*. This one is chosen as the critical unit operation. The identified critical unit is the reactor, in all designs. Improvement in critical unit reliability calculated for a duration of a week results in a better reliability for the process as a whole as well as for the unit alone. The process reliability of the base design, Figure 1a, is improved from 0.9855 to 0.9871 after decreasing the reactor failure rate from 1.55E-3 to 1.55E-5. The sensitivity of the *EPP* is calculated according to SI_{EPP-R} and is equal to -1.043. The negative value for *SI* indicates a decrement in the *EPP* through the process reliability increment. The same trend is employed for the improvement in the reliability in the other two designs. The results show that their SI_{EPP-R} are -1.186 and -0.877 (Table 3).

It is difficult to compare SI_{EPP-n_u} and SI_{EPP-R} as they have different bases of design and reliability, respectively. If the base for all of the calculated *SI*s were a dollar value, a detailed comparison would be possible, e.g. cost of maintenance for the reliability parameter and cost of design change for the design parameter. The $SI_{EPP-n_u \& R}$ is also non-comparable to any other *SI*s. However, the $SI_{EPP-n_u \& R}$ value reveals that process owners can achieve the lowest *EPP* by incorporating changes in both design and reliability parameters in a process. However, the cost of such changes needs careful review.

5 CONCLUSION

In this paper a new EPE methodology has been employed to compare three different process designs for formaldehyde production in terms of their environmental impact. The advantage of this comparison over the traditional ISD route selection is the ability to acknowledge uncertainties and the use of a PIH calculation. Then, a sensitivity analysis is conducted to detect the influence of model inputs and their variations over the output variations. The results show that the lowest *EPP* is obtained with improvements over the design and reliability. However, knowing the best process design may not be helpful if the plant is already constructed. Therefore, a reliability improvement is proved to be a beneficial factor to gain a lower *EPP* for already constructed processes. This approach may be cost effective and environmentally beneficial, which makes it desirable for process owners, as only maintenance cost is added which in a chemical process is smaller than

5% of the sale revenue [Orica Limited, 2011]. In order to further investigate the financial aspect of this model, a multi-objective optimization is proposed in the future work based on *EPP* and profitability objectives which allows the decision makers to consider the environmental and economical targets at the same time.

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