AN ENGINEERING-BASED ENVIRONMENTAL MANAGEMENT SYSTEM DESIGN

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ABSTRACT
Environmental imperatives necessitate formal Environmental Management Systems (EMS) to understand and manage the environmental consequences of commercial activities. A diverse range of EMS have been proposed, however these present limitations in accommodating changes in environmental performance, and do not incorporate fundamental process analysis to assess how the actual performance varies from what is theoretically achievable. A novel engineering-based risk evaluation framework has been developed that applies fuzzy logic and fundamental process analysis to overcome the identified issues.

Keywords: EMS; environmental management systems; process variation; fuzzy logic; Chemical processing plant design.

1 ENVIRONMENTAL PERFORMANCE MEASURES

Sustainable development "meets the needs of the present without compromising the ability of future generations to meet their own needs" [1]. Corporations are increasingly focusing on sustainability by the adoption of Environmental Management Systems (EMS) [2,3,4,5]. A diverse range of EMS exist for the evaluation of the operational environmental performance of a product or industrial process, including [6,7]:

- Environmental Reporting Frameworks
- Economic Input–output Tables
- Life Cycle Assessment
- Ecological footprint analysis
- Full Cost Accounting
- Sustainability Assessment Modeling

These EMS fail to incorporate fundamental process analysis, and do not readily evaluate changes in environmental performance owing to process variation (e.g. changes in the production rate of the process), and investment in new techniques and practices (e.g. pollution abatement technologies, or technologies to increase process efficiency). In addition, many of the existing methods of environmental operational performance do not accommodate the uncertainties associated with the available data and applied modeling techniques.

This work presents a novel conceptual framework for operational environmental performance evaluation for an industrial process or product. This framework aims to overcome limitations identified in existing methods by the integration of fundamental process modeling with risk assessment using fuzzy logic techniques.

2 FUZZY LOGIC

A Boolean membership function (μ) indicates whether a value (x) belongs to a certain state, or set. Conventional set theory uses binary memberships, and the membership function of the set A, μA, is defined as:

- $\mu A(x) = 1$ if x is a member of set A
- $\mu A(x) = 0$ if x is not a member of set A

Fuzzy sets overcome the rigidity of conventional set theory by expanding the definition of a membership function to allow the degree of membership of a set to lie between 0 and 1 [8]. In fuzzy logic, the truth-value, $T(x)$, is a measure of the veracity of a proposition, and can be *any value* between zero and one. This is in contrast to Boolean logic, where truth-values must be *either* zero or one, i.e.

either true or false. Fuzzy logic allows the combination of information from different sources, while enabling approximate reasoning in the presence of uncertainty [9,10].

The form of the fuzzy membership function is unrestricted, but may be trapezoidal, Gaussian and Dirac-delta forms [11]. Figure 1 illustrates how the boundaries on the fuzzy set create areas of overlap between the various states. For example, the crisp input of daily production rate of 66 tonnes per day has a membership of 0.8 to the 'medium' category, and membership of 0.2 to 'high' category. By allowing for degrees of membership in different sets, fuzzy logic can decrease the potential error in associating a particular value with a particular state.

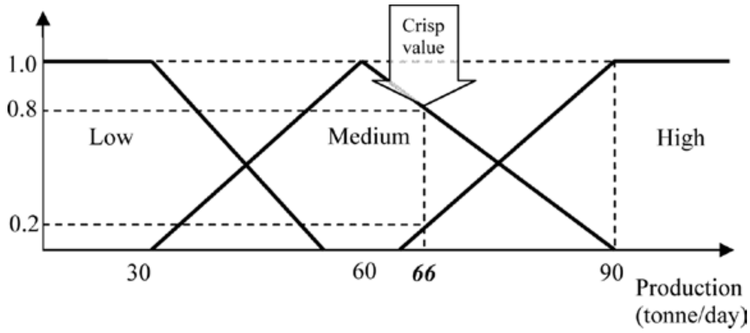

Figure 1 Overlaps Between Fuzzy Sets, after (Burvill et al*. 2010).*

2.1 Fuzzy Inference Systems

Fuzzy inference systems map a specified input to an output using fuzzy logic based on fuzzy membership functions, conditional statements (*If-Then* rules) and fuzzy operators. A series of inference systems are available [6]. The Mamdani inference method is used in this work as it: provides a framework for incorporating *If-Then* rules and it allows for inputs and outputs to be physical variables and is therefore applicable to engineering-based systems. The fuzzy logic framework consists of four stages:

- Fuzzification of data
- Transformation of data via an inference system
- Composition of transformed data
- De-fuzzification into crisp values

2.2 Fuzzy Logic Risk Assessment

Evaluation of the risk posed by the environmental aspects of an industrial process is a complex undertaking involving significant uncertainties [12]. Such uncertainties lead stakeholders to define risk parameters in qualitative linguistic terms [13]. Fuzzy logic was designed to interpret the uncertainties of real-world situations, and can allow approximate reasoning based on qualitative linguistic descriptors [14]. Fuzzy logic has been applied to accommodate the inherent uncertainties of environmental risk assessment in various fields, for example: water contamination [15,16], and offshore drilling waste [17]. However, an extensive literature review failed to identify evidence of prior application of fuzzy logic to fundamental process analysis where the risks stemming from the environmental aspects of industrial products or processes are quantified.

3 APPLYING THE ENGINEERING-BASED RISK EVALUATION FRAMEWORK

This section describes an application of the conceptual engineering-based risk evaluation framework to an existing, operational chemical processing plant. The case study will:

- Demonstrate the framework with real process data
- Explore the strengths and limitations of the framework
- Identify areas for further development of the framework

A formaldehyde (CH3OH) manufacturing process is examined. Formaldehyde is toxic by inhalation, and a suspected carcinogen. In production, formaldehyde (and water) is formed by the oxidation of methanol on a metallic oxide catalyst (Equation 1, Figure 2):

$$CH_3OH + \frac{1}{2}O_2 \rightarrow H_2CO + H_2O \qquad (1)$$

A fixed-bed vapour-phase oxidation reactor is used to produce formaldehyde. The reaction is exothermic, with heat removed from the reactor by a boiling liquid heat transfer medium.

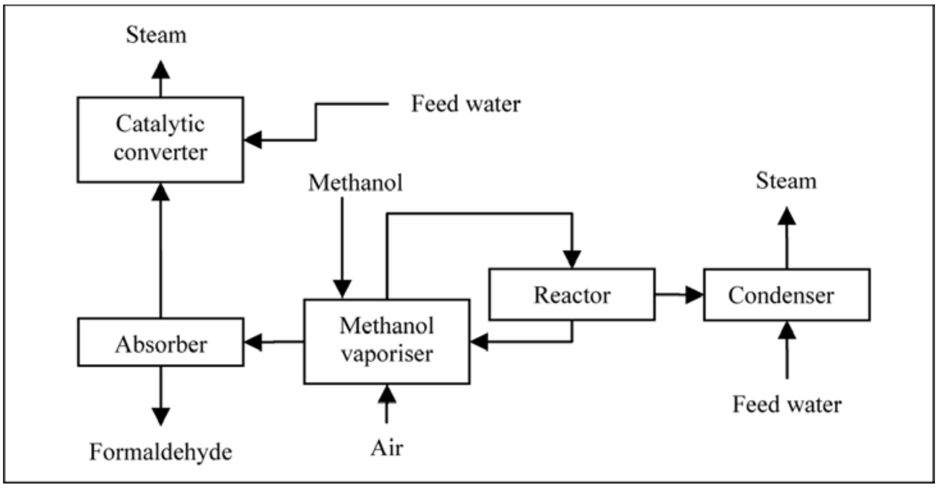

Figure 2. Simplified Manufacturing Process Flow Diagram, after (Burvill et al. 2010).

4 FRAMEWORK SUMMARY

The conceptual framework proposed in this work contains fuzzy models of the process, scenario and associated risks.

4.1 Fuzzy Process Model

Fuzzy rules can be used to model the relationships between the input and output streams of the industrial process under consideration. This allows information about the physical flows associated with a process, and the natural variations that occur within a process to be introduced to the consequence and risk models to determine the risk posed by hazardous scenarios.

4.2 Fuzzy Scenario Model

A fuzzy scenario model is developed for each potentially hazardous scenario. Each fuzzy scenario model relates the operating regime of the plant to the consequences owing to the environmental aspects of the associated hazard scenario.

4.3 Fuzzy Risk Model

These consequences are then related to an estimate of likelihood of that scenario using a fuzzy risk model. The consequences of the hazardous scenario are expressed in financial cost terms, and relationships are developed for each scenario to estimate consequences in five categories:

1. Environmental
2. Health and safety
3. Loss of corporate reputation
4. Business interruption
5. Business liabilities

The proposed framework is a novel application of the well-established discipline of expert systems. An expert system simulates a human specialist's knowledge and reasoning [18]. Expert systems comprise a set of rules that analyse information about a specific class of problems, and provide mathematical analysis of the problem being considered. It is anticipated that a team of relevant experts within the organization would be engaged in the future development of the proposed framework to provide a realistic determination of the relevant consequence cost types to be included in the scenario model, and the relationships between the scenario input variables and these cost types.

4.4 Scenario Model: Liquid spill

A fuzzy scenario model was developed to compute the consequences of a potential fugitive liquid emission scenario, such as a spill or leak from a particular process stream.

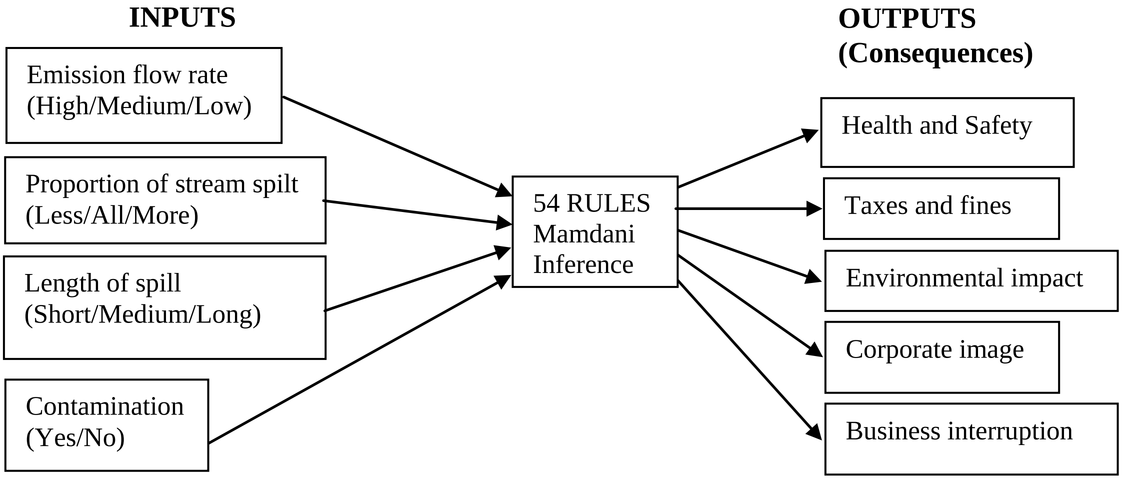

Figure 3. Model for a fugitive liquid emission.

The consequences of this scenario have been determined, in consultation with plant personnel, to be dependent on the following factors:

1. The normalised flow-rate of the fugitive emission at the time of the emission, in this case, the formaldehyde product output stream is considered.
2. The proportion of the process stream that is spilt or leaked from a process stream.
3. The length of time of the spill.
4. Whether or not ground contamination occurs, that is whether any physical barriers that may be in place around the plant to prevent ground contamination (for example, bunding).

Other factors that may influence the consequences of this scenario include the surrounding population densities and the sensitivity of the surrounding environment. Again, the flexibility of the model allows for the inclusion by the developer of these factors as inputs to the scenario model as deemed appropriate.

Input variables for the fuzzy scenario model for a liquid fugitive emission are:

1. The “normalised emission flow-rate”, determined from the process model [6], which may be High, Medium or Low. The emission flow rates are normalised with respect to the maximum emission flow rate.
2. A “proportion of stream spilt” factor, indicating whether such an emission is likely to be 'Less' than, 'All' of, or 'More' than the relevant stream's flow rate under normal operating conditions (Figure 4). If it less than the entire stream is spilt, an input of 0.5 should be entered into the model, if all the entire flow rate is leaked, a value of 1 should be entered, and if more than the normal operating flow rate is expected to be leaked, a value of 1.5 should be entered.
3. A “length of spill” factor, to indicate the time duration of the spill, is defined here as 'Short', 'Medium' or 'Long' (Figure 5).
4. A “ground contamination” factor with membership functions shown in Figure 6. If contamination is expected, an input value for this variable of 1 should be entered into the model, and if no contamination is expected this variable should have an input value of 2. Again, the membership functions have been given a finite width purely for computational reasons, to ensure the input is assigned to the correct category.

Fuzzy logic rules were composed to define the relationship between the input variables and the outputs using the Mamdani inference method. The outputs of the model are the five categories of consequence, in cost terms, to the company and society (figure 3). In this model, only fines are considered when assessing business liabilities. Both internal costs to the company due to the environmental aspects of the scenario, and external costs to society should be included where possible, and appropriate membership functions should be defined for each of these costs, allowing for higher standard deviations of the membership functions for those cost types with more uncertain consequences.

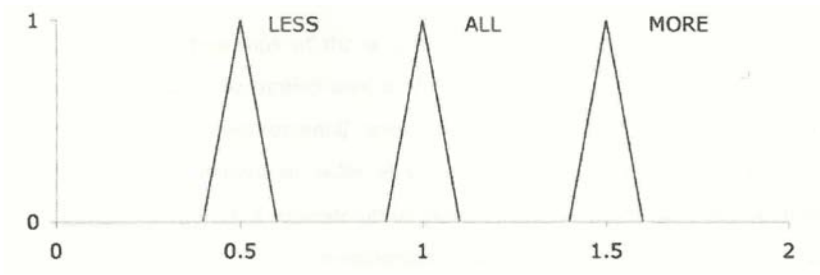

Figure 4. Input membership functions for proportion of stream spilled.

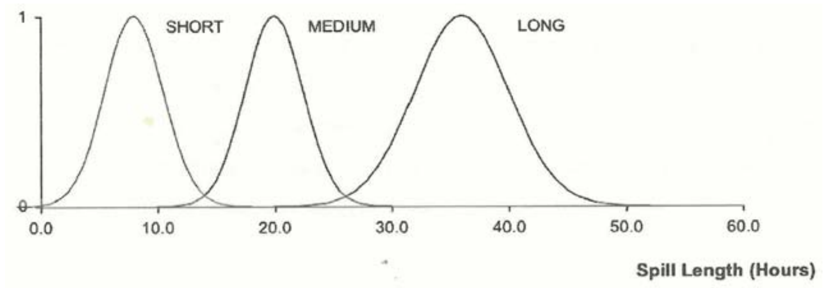

Figure 5. Input membership functions for time duration of a liquid spill.

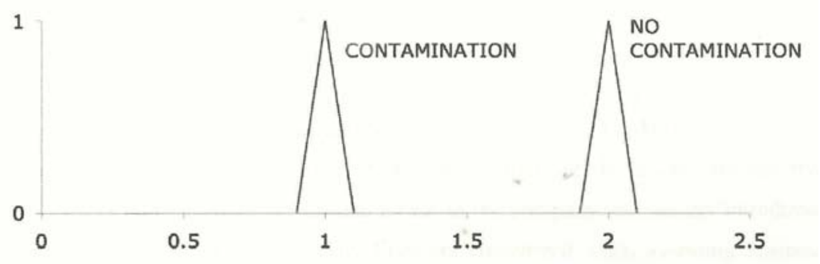

Figure 6. Input membership functions for liquid contamination.

To allow for every combination of the input variable membership, 36 rules have been constructed in MATLAB™ [7]. Each rule then relates the particular combination to the relevant membership function of each output variable. The relationships contained within the fuzzy inference system model rules are presented in Tables 1 to 4. Pertinent example rules:

Rule 3: If normalized emission flow-rate is *Low* and proportion of stream spilt is *Less* and Length of spill is *Long* and *Contamination occurs*: Then consequences due to: liabilities are *Very Low* and environmental remediation is *Low* and safety and health are *Very Low* and corporate image is *Zero* and business interruption is *Very Low*.

Rule 26: If normalized emission flow-rate is *High* and proportion of stream spilt is *More* and Length of spill is *Medium* and *Contamination occurs*: Then consequences due to: liabilities are *Medium* and environmental remediation is *Very High* and safety and health are *High* and corporate image is *Very High* and business interruption is *Low*.

Rule 28: If normalized emission flow-rate is *Low* and proportion of stream spilt is *Less* and Length of spill is *Short* and *No Contamination occurs*: Then consequences due to: liabilities are *Zero* and environmental remediation is *Zero* and safety and health are *Zero* and corporate image are *Zero* and business interruption is *Low*.

Table 1. Inference rules for potential liabilities due to fines

			No ground contamination			Ground contamination		
			Emission flow rate (normalized)					
			Low	**Medium**	**High**	**Low**	**Medium**	**High**
Short	**Spill proportion**	**Less**	Zero	Zero	Zero	Zero	Very Low	Low
		All	Zero	Zero	Zero	Very Low	Low	Medium
		More	Zero	Zero	Zero	Low	Medium	High
Med		**Less**	Zero	Zero	Zero	Very Low	Low	Medium
		All	Zero	Zero	Zero	Low	Medium	High
		More	Zero	Zero	Zero	Medium	High	VeryHigh
Long		**Less**	Zero	Zero	Zero	Low	Medium	High
		All	Zero	Zero	Zero	Medium	High	VeryHigh
		More	Zero	Zero	Zero	High	VeryHigh	Ext. High

Table 2. Inference rules for potential liabilities due to safety

			No ground contamination			Ground contamination		
			Emission flow rate (normalized)					
			Low	**Medium**	**High**	**Low**	**Medium**	**High**
Short	**Spill proportion**	**Less**	Zero	Zero	Zero	Zero	Zero	Very Low
		All	Zero	Zero	Very Low	Zero	Very Low	Medium
		More	Zero	Very Low	Low	Very Low	Low	Medium
Med		**Less**	Zero	Zero	Very Low	Zero	Very Low	Low
		All	Zero	Very Low	Low	Very Low	Low	Medium
		More	Very Low	Low	Medium	Low	Medium	High
Long		**Less**	Zero	Very Low	Low	Very Low	Low	Medium
		All	Very Low	Low	Medium	Low	Medium	High
		More	Low	Medium	High	Medium	High	VeryHigh

Table 3. Inference rules for potential liabilities due to corporate image

			No ground contamination			Ground contamination		
			Emission flow rate (normalized)					
			Low	**Medium**	**High**	**Low**	**Medium**	**High**
Short	**Spill proportion**	**Less**	Zero	Zero	Very Low	Zero	Zero	Low
		All	Zero	Zero	Low	Zero	Very Low	Medium
		More	Zero	Very Low	Medium	Zero	Low	High
Med		**Less**	Zero	Zero	Low	Zero	Zero	Medium
		All	Zero	Very Low	Medium	Zero	Low	High
		More	Very Low	Low	High	Very Low	Medium	VeryHigh
Long		**Less**	Zero	Zero	Medium	Zero	Zero	High
		All	Very Low	Low	VeryHigh	Very Low	Medium	VeryHigh
		More	Low	High	VeryHigh	Low	VeryHigh	Ext. High

Table 4. Inference rules for potential liabilities due to business interruption

			No ground contamination			Ground contamination		
			Emission flow rate (normalized)					
			Low	**Medium**	**High**	**Low**	**Medium**	**High**
Short	**Spill proportion**	**Less**	Very Low	Very Low	Very Low	Very Low	Very Low	Very Low
		All	Very Low	Very Low	Low	Very Low	Very Low	Low
		More	Very Low	Low	Low	Very Low	Low	Low
Med		**Less**	Very Low	Very Low	Low	Very Low	Very Low	Low
		All	Very Low	Low	Low	Very Low	Low	Low
		More	Low	Low	Low	Low	Low	Low
Long		**Less**	Very Low	Low	Low	Very Low	Low	Low
		All	Low	Low	Low	Low	Low	Low
		More	Low	Low	Medium	Low	Low	Medium

Figure 7 shows the model output for the environmental remediation consequences for a liquid spill causing ground contamination, for the full range of normalized emission flow-rates and for different levels of process stream spill proportion. The consequence due to environmental remediation peak at the highest process operating rate, when the proportion of stream split is more than the expected stream flow rate at normal operating conditions. The model calculates an approximate figure of $2 million dollars for this peak. In order to improve this estimate, historical information on remediation costs from previous spills that have occurred within, and external to the company should be analyzed. If no contamination occurs, the model output is a plane through zero on the remediation consequence axis.

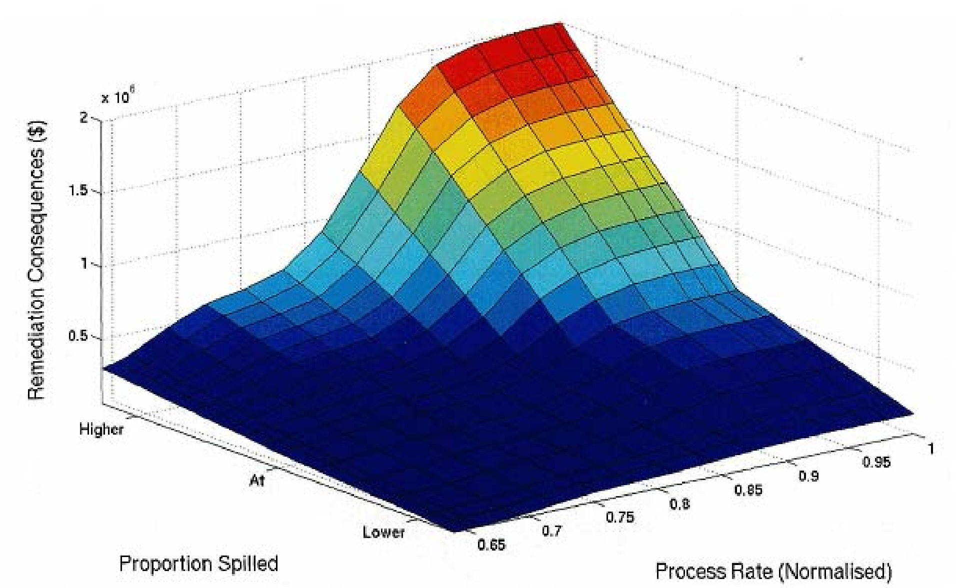

Figure 7. Environmental remediation consequences for a liquid spill causing ground contamination.

Figures 8 and 9 show the corporate image cost consequences for a spill that causes contamination, which are expected increase significantly with the length of the spill (which is a parameter that influences the total amount spilled). In both cases, corporate image consequences peak for high process operating rates when the proportion of the stream spilled is more than the expected flow rate of the stream under normal operating conditions.

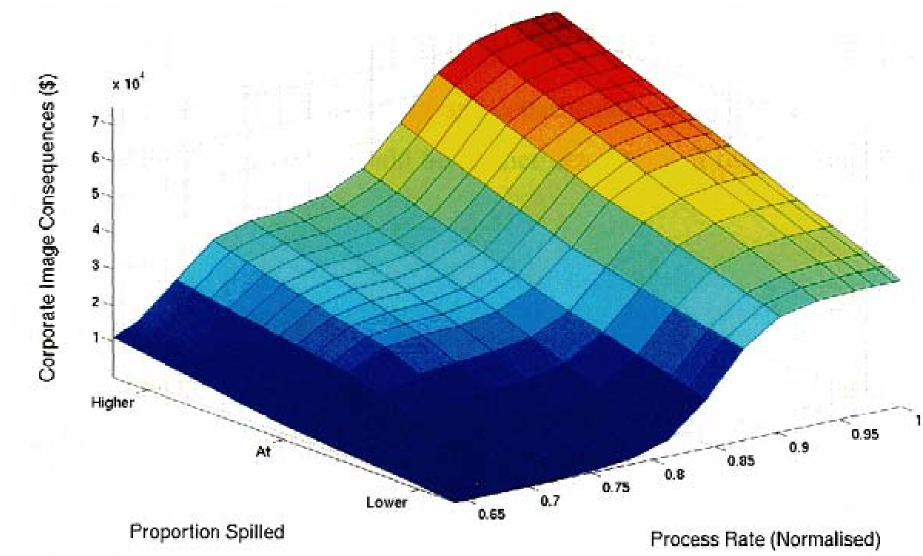

Figure 8. Corporate image consequences for a medium length liquid spill causing ground contamination.

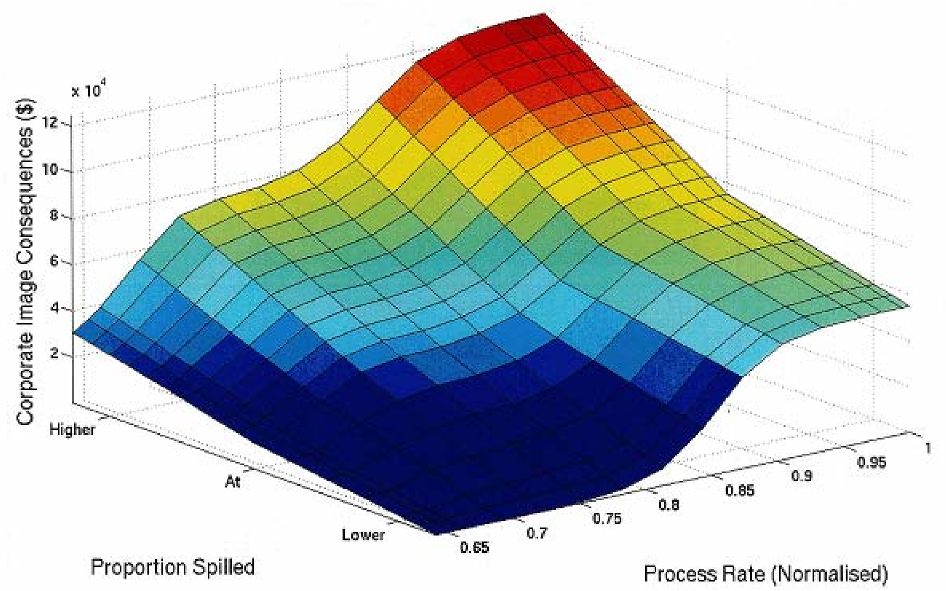

Figure 9. Corporate image consequences for a long liquid spill causing ground contamination.

The main purpose of the scenario modeling carried out here is to illustrate the flexibly of the framework. The framework allows a full range of consequence cost types to be individually predicted from the process operating rate and other scenario variables, and aggregated when appropriate (for example, consequences due to fines and consequences due to taxes have been aggregated into the category of business liability consequences). In addition, membership functions can be defined individually for each cost type, to represent the accuracy of the predicted relationships between the scenario input variables and a particular cost type.

5 CONCLUSIONS

This paper has presented an outline of the current development of an engineering-based environmental performance framework design. The framework is at present focused on the chemical engineering sector, due to the ongoing collaboration between university researchers and a leading Australian chemical manufacturer.

The paper outlines a case study completed using the framework in the context of a chemical processing plant and the consequences of a hazardous liquid spill. This case study combines fundamental engineering analysis of the chemical process with risk assessment using fuzzy logic modeling techniques.

First, a fuzzy process model, based on historical plant operating data, was developed to model the relationships between the physical flows of process inputs (in this case methanol, water, air) and outputs (gaseous emissions and the formaldehyde product). A fuzzy scenario model was developed to illustrate the calculation of the consequences of a fugitive gaseous emission. Finally, a fuzzy risk model was created to combine the consequences calculated using the fuzzy scenario model with an estimate of scenario likelihood, to calculate a level of risk.

The engineering-based fuzzy risk assessment framework has been shown to:

- Use fundamental engineering analysis to incorporate information about the process operation level, and the variations that occur within a chemical process plant.
- Be flexible – it can be adopted by the developer to include a wide range of consequences owing to both the environmental and the social aspects of a production facility.
- Be transparent – estimations and assumptions in the scenario modeling are made by the developer and user, and the uncertainties associated with these are captured in the fuzzy membership functions of model's variables.

Although this method is at a preliminary stage of development, it demonstrates clearly the proposed concept and the in-principle applicability of the framework to a chemical processing plant. The completeness of the method would depend on investment by an organization on its construction and maintenance. For example, potential improvements to the scenario and risk modeling of the formaldehyde manufacturing process used in this case study include:

- Refining the membership functions of the scenario model variables and the scenario model rules including all relevant cost types for each cost category.
- The development of a complete list of hazardous scenarios for the process and the development of the relevant scenario models.
- To reduce the resources required to implement the model, scenario rules for common processing plants could be developed.
- The model could be modified to receive live information about the risks associated with a particular process, enabling plant operators and managers to use it as a monitoring tool.

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