Int.J.Curr.Res.Aca.Rev.2016; 4(4): 51-60

EXCELLENT PUBLISHERS

International Journal of Current Research and Academic Review

ISSN: 2347-3215 Volume 4 Number 4 (April-2016) pp. 51-60

Journal home page: http://www.ijcrar.com

doi: http://dx.doi.org/10.20546/ijcrar.2016.404.006

Dependent Environmental Indicators and Their Effect of Ranking

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KEYWORDS

Environmental Indicators, world's ecological system, harmful chemicals.

A B S T R A C T

The adverse effect on the environment is mainly due to the release of harmful chemicals that affects the world's ecological system. The concentrations of these chemicals are considered as the main indicators for environmental assessment. In some cases, environmental indicators are highly dependent and their inclusion will increase the size of experimental data to be collected and studied. Moreover, it will also increase computational time. This paper will answer the question if dependent indicators should be included when environmental decision making is to be made through ranking. It presents a methodology to implement simple tests on environmental indicators to check if their inclusion in the decision-making exercise is essential. A case study on desalination plants in the Arabian Gulf area will be presented. Although different and advanced desalination methods are being used, their environmental effects need to be assessed and a reliable methodology needs to be assessed and a reliable methodology needs to be established to identify existing harmful plants. The problem of insufficient data for decisions on desalination plants is resolved by identification of dependent indicators.

Introduction

Environmental aspects include potential damage to local and regional environment including humans. Over the last 30 years, there has been a very rapid growth in environment related legislations affecting chemical and power industry. The relation between the industry performance and the environment are complex and not fully understood. The balance recourse used and benefits yield are an individual and social judgment and is clearly difficult to quantify (Sharrat, 1999). Selecting an appropriate set of indicators to represent multiple and sometimes disparate values is particularly challenging because the interpretation of impacts depends on indicator roles and relationships among indicators (Glenn *et al.*, 2016). However, environmental regulations and indicators are widely used. Using potential ecological indicators is important in assessing ecological risk and/or impact evaluations from observations at a molecular level (Jin-Soo, 2015). Regulations now cover products, air and water quality, waste disposal, soil reclamation, noise abatement and related matters. Environmental indicators cover wide range of aspects. However, the most important amongst these is chemical effect and/or concentration. Industrial chemical risk ranking has received the most attention, and several systems have been used, for example, to determine which chemical/location should have more environmental regulations. Davis *et al*. (1994) gave a good review of 51 chemical ranking and scoring systems. They presented, among others, the system method or algorithm, chemicals and data selection approach together with literature resources for ranking chemicals. Strengths of several certification schemes can be combined with research-based indicators, to increase the reliability of environmental assessments (Markus, 2014).

The problem that is usually associated with the environmental indicators is data availability. Environmental justice efforts suffer from incomplete data (Lobdell *et al*., 2011) and in some special cases the abundant data will result in developing techniques to reduce the model complexity and selecting a model subset data from experiential data (see for example Pavan *et al*., 2005). This requires preparing as small as possible data set before doing any environmental decision making. The existence of dependent environmental indicators encourages the reduction of data set and this will be studied in this work.

Dependent Environmental Indicators

The selection of appropriate measures of environmental performance for a process will depend on the nature of the environmental concerns, type and quantity of information available and degree of accuracy required in the representation. Several environmental analysis indicators or attributes have been developed, some of them are internationally known and proven. Some have been used and developed inside companies. The different environmental indicators are suitable for different stages of process development, design and operation. Some can be applied at a very early stage of planning and require an overall knowledge of the system under consideration, and some must be applied onto existing units with full knowledge of all aspects of the unit. It is clear that irrelevant and redundant indicators should be eliminated from environmental analysis or decision making. However, a question is raised: should dependent indicators be eliminated?

In the science field, dependent variable is the variable expected to change whenever the independent variable is changed and correction can be obtained between them. Methods for correlation between data are generally classified as statistical or conceptual. Statistical methods are oriented towards numerical data and create characterization in terms of correlation, statistical distribution, variance (Imam *et al*., 1993). Conceptual methods are oriented towards qualitative data and rules. Environmental assessment can benefit from consideration of the correlation structure among indicators (Sutherland *et al*., 2016) and this will help in reducing data collection for the assessment and can provide information about the underlying system and help in constructing a more appropriate environmental model. Dependency between environmental indicators are studies widely in environmental assessment, for example, between dissolved oxygen and pH (Makkaveev, 2009), CO_2 emission and energy consumption (Omri, 2013) and in watersheds (Sutherland *et al*., 2016).

Piegorsch and Bailer (2005) showed that environmental data can be modeled as linear, multiple-linear and simple nonlinear models. Al-Sharrah (2011) indicated that when chemicals are studied and they are ranked according to their hazardous effect, the indicators (Y_1, X_1, X_2) (e.g. threshold limit value, lethal dose ... etc.) can be correlated using multiple linear correlation with a correlation parameter.

$$Y_1 = \rho X_1 + \sqrt{(1-\rho^2)}X_2$$

The Y_1 indicator will have a correlation of ρ with the X_1 indicator, i.e., statistically, Y_1 is more significantly correlated to X_1 than X_2. It is worth mentioning that correlation between environmental data can be known from an expert knowledge of the system or by statistical methods (e.g. covariance) applied on the environmental data.

Ranking for Decision Making

Decision-based ranking and scoring systems can be used to focus attention and resources on the largest potential risk or gain. The decision is usually the final stage of an exercise which started with data collection of some objects and their corresponding indicators. Examples of objects include projects, chemicals, databases etc. and examples of indicators include prices, environmental releases, physical properties etc. The decision on these objects is to determine the most important objects that cause high loss and thereafter needs attention and/or modification.

Decision-based ranking is used extensively in environmental analysis. Studies include ranking projects (Brans *et al*., 1986), environmental databases (Brüggemann and Voigt, 1995), pesticides (Halfon *et al*., 1996), sediment sites (Brüggemann *et al*., 2001). Industrial chemical risk ranking has received the most attention, and several systems have been used, for example, to determine which chemical plant should have more environmental regulations.

In general, ranking method can be classified as *relative ranking* and *categorize* methods. *Relative ranking* means that an overall rank or score is derived for the objects relative to one another and *categorize* means that groups of objects are assigned high medium or low rank or selected, non-selected objects, using different comparisons between their indicators. Examples of *relative ranking* are Copeland method (Al-Sharrah, 2010), Simple Additive Ranking (SAR) and examples of *categorize* methods are Hasse diagram (Halfon & Reggiani, 1986). Some of the methods are parametric methods i.e. that a decision maker should provide information or judgment to combine the different indicators in order to obtain the rank. A simple example is when weights assigned to the indicators are to be in a form suitable to be aggregated into a single number from which a rank can be obtained. SAR is simply ranking of objects with respect to each indicator separately, and then subsequent aggregation of the weighted ranks by arithmetic mean. The Hasse diagram and the Copeland method are considered non-parametric method that have been used extensively in decision-based ranking, for example (Brüggemann and Voigt, 1995). A representation of the decision making from SAR with equal weights and Copeland are presented in Figure 1. Both of these methods depend on comparison of indicators however their final results may differ.

Other useful and simple relative or total ranking methods are discussed in (Pavan and Todeschini, 2004). For R indicators and I objects and possible weights w for the indicators, the following are two widely used total ranking methods:

Desirability Function

The approach of the desirability function is to define a desirability function for each indicator in order to transform values *y* of the indicator to some scale

$$d_r = f_r(y) \qquad 0 \leq d_r \leq 1 \qquad r = 1,2,\cdots,R$$

The overall desirability is calculated by combining all the desirability through a geometrical mean.

Utility Function

The approach is very similar to the desirability function; each indicator is independently transformed into a utility function. However, subsequent aggregation of the weighted function is done by an arithmetic mean.

Methodology

As mentioned earlier, correlations relating environmental data recommended by Piegorsch and Bailer (2005) are linear, multiple-linear and simple nonlinear models. Our specific approach in studying dependent environmental indicators is to know which type from the above correlations affects environmental decision making when it is done by ranking. First, random data were used to provide the above mentioned dependencies and later decision making was generated from the data using different ranking methods; and finally case studies will be presented using real data.

Three types of models between environmental data will be studied, linear:

$$Y_1 = a_0 + a_1 X_1 + \varepsilon_1$$

Where Y_1, X_1 are environmental indicators, a_0, a_1 are model parameters and ε_1 is the additive error term and

Multiple linear

$$Y_1 = \rho X_1 + \sqrt{(1-\rho^2)} X_2$$

Where ρ is the correlation coefficient.

Simple Non-linear

$$Y_1 = a_2 X_1^2 + \varepsilon_1$$

At this stage of analysis, random numbers will be used to test the effect of environmental correlations on decisions-making. Steps are as follows:

1. Original Data: Sequences of uncorrelated normal distributed random indicators X_1, X_2,..X_n *for* hypothetical objects Obj_1, Obj_2, …Obj_m are generated using Excel.

2. Extended Data: A correlation model is selected and a dependent indicator Y_1 is calculated for all objects using that correlation.

3. Decision ranking: Ranking is obtained using the original and extended data. Results of ranking will place the objects (assigned a numerical rank) from top to bottom to represent the most and the lease important object i.e. decision-making.

4. Comparison: Ranks from original and extended data are compared using the Pearson product-moment correlation Coefficient (PPMC).

Random data were generated using Excel with sizes up to 10 objects with 8 indicators. To apply the Copeland ranking method, a program was written in MATLAB (2010); however for other ranking methods, the computations were performed using the DART (2010) software. These methods include Desirability, Utility~~,~~ and Simple additive ranking.

Results show that ranking results were not highly affected by the addition of a correlated data. The PPMC ranged from 0.9805 to 0.9238 and this means that if correlated environmental data exist in a decision making exercise, their exclusion will not affect the ranking of objects in the exercise. This is very helpful in cases of incomplete data sets and/or for large data sets. The following case study will present this result on real data.

Case Studies

Desalination plants and their environmental impact into seawater

Desalination was first used by Greek sailors in the 4th century BC to create drinking water by evaporating seawater. Today there are many technologies used for desalination that can process more than 1 million cubic meters per day. The selection of the desalination process is typically based on different operational parameters such as the availability of a raw water or energy source (e.g., seawater vs. brackish water or low-cost heat vs. electricity), the product water demand, intended use and product water quality specifications (industrial vs. municipal use), or the technical know-how, capacity and costs to build, maintain and operate the plant (Tsiourtis, 2001).

The two main desalination technologies are membrane by Reverse Osmosis (RO) and Thermal by Multi Stage Flash (MSF) desalination. Reverse Osmosis (RO) desalination uses the principle of osmosis with hydraulic pressure as a driving force to remove salt and other impurities, by transferring water through a series of semi-permeable membranes. Multi Stage Flash (MSF) desalination uses heat to evaporate and condense water to purify it through different stages with different pressures. Other new technologies are emerging now such electrodialysis as (ED) pressure-retarded osmosis (PRO). These new technologies need to be evaluated against the existing ones in terms of sustainability, efficiency and reliability.

The increase~~s~~ in desalination plants in many sea regions especially in the Arabian Gulf and the growing number of industrial-sized facilities raises concerns over potential negative impacts of the technology on the environment. The impacts of a seawater desalination plant on the marine habitat depend on the physical and chemical properties of the discharge streams. Therefore, a good knowledge of both the effluent properties and the receiving environments is required in order to evaluate the potential impacts of desalination plants on the marine environment which has a considerable amount of uncertainty.

This work is aimed for environmental assessments and decision making framework for desalination plants using data about the chemical and physical discharges into the sea and their marine ecological effects. The assessment is done using ranking. Special attention is given to the Arabian Gulf where 50% of worldwide seawater plants operate. Desalination of water is an important method for solving water shortage in Arabian Gulf countries; however, its adverse environmental effects have started appearing in shallow Arabia Gulf.

Several issues must be addressed for any environmental evaluation of desalination. The resulting brine must be disposed off in such a way with minimum impact to the environment. All desalination plants use chemicals as part of the pre-treatment process of the feed water, and for post-treatment process of product water. This practice results in discharge of liquid wastes such as disinfectants (Chlorine and biocides), de-fouling and antiscalant agents along with the brine.

Discharged brine contains low concentrations of metal ions resulting from corrosion, namely copper, nickel, chromium and iron. These concentrations are profoundly increased with acid cleaning of the plants.

In desalination studies, the effects on environment are studied to a limited extent. Roberts *et al*. (2010) noted that a large proportion of the published work is descriptive and provides little quantitative data that can be assessed independently. Most studies study temperature, salinity, chemical disposals and temperature. Water temperature is one of the most important characteristics of sea environment, affecting dissolved oxygen and chemical and biological processes. Dissolved oxygen and temperature are two fundamental measurements of sea productivity and health with clear dependent relation between them. Also, it is shown that the changes of the pH values are nonlinear relative to the content of oxygen (Makkaveev, 2006).

Bu-Olayan and Bivin (2006) has reported trace metal levels in sea water from five sites of Kuwait Bay where many desalination plants are present.

They reported five metals during harmful algal blooms and non-harmful algal bloom for both seawater and ctenophore? samples in two seasons, summer and winter forming a data matrix with 5 objects (sites) and 40 indicators (5 metal concentration in 2 samples in 2 seasons). The metal concentrations are highly linearly correlated and if this data is used for ranking sites, then a reduction can be done using one of the metals only.

This leads a reduced data matrix of 5 objects (sites) with 8 indicators (metal concentration in 2 samples in 2 seasons). Results from both the original and reduced data matrix gave the same decision making; ranking sites from most contaminated to the lowest as: Site-III (Khanma) - Site-IV (Towers) - Site-V (Salmiya) - Site-II (Doha) - Site-I (Subiyah).

Another case study is based on the data studied by Modamed et. al, (2005) and shown in Table 1.

The indicators are the rows of Table 1 and the objects to be ranked are the columns and they represent desalination plants in the GCC area. It is clear that some data are missing from Table 1 and if a decision is to be made about which of the above plants are affecting the environment, the problem of missing data should be solved.

Alternatively, a good justification has to be given to exclude the incomplete indicators. It would be possible to exclude incomplete indicators if a relation can be found with other indicators or if they are irrelevant to the environmental objective. Starting with SiO_2, this chemical is considered to be safe by the world health organization (WHO) and it's actually a dietary requirement for various organisms; therefore it can be safety excluded from the environmental analysis.

The next is Carbonate (CO_3^-), this ion together with the bicarbonate is highly correlated to the pH (Holmes-Farley, 2002). Therefore, it can be removed from the data set before ranking the plants. Using all the discussed ranking methods i.e. Copeland, SAR, Utility and desirability ranking results indicate that the desalination plants can be ranked from most hazardous to the lowest as: Umm Alquain, Alssadanat, then Hamriyah.

Table.1 Chemical Composition of Reject Brine from Inland Desalination Plants in GCC Countries (Mohamed *et al.*, 2005)

Parameter	Alssadanat, Oman	Umm Alquain, UAE	Hamriyah, Sharjah, UAE
Ca^{++}, mg/l	923	202	173
Mg^{++}, mg/l	413	510	311
Na^{++}, mg/l	2780	3190	1930
K^{++}, mg/l	81.5	84.5	50.7
Sr^{++}, mg/l	28.2	21.1	14.2
Sum cation, meq/l	203.06	192.98	119.48
pH	7.21	7.54	7.66
Electrical conductivity, mS/cm	16.8	14.96	127.41
TDS, mg/l	10553	10923	7350
NO_3, mg/l	7.2	27.4	15.9
F^-, mg/l	0	1.6	1.3
Cl^-, mg/l	4532	4108	2933
SO_4, mg/l	1552	2444	1537
SiO_2, mg/l	NA	164.09	133.71
Carbonate (CO_3^-)	NA	NA	NA
Bicarbonate (HCO_3^-)	466	656	753
N^-	1.6	6.2	3.6
Sum anions, meq/l	167.88	198.05	127.41
Ion balance	9.48	4.02	-3.21
SAR	19.12	27.2	20.3
SER	59.55	71.91	70.27
L.I	1.24	1.04	1.26
R.I	4.73	5.46	5.14
Total ion, mg/l	10781	11245	7719
Total alkalinity	380	538	617
Total hardness	4041	2630	1730
Fe, meq/l	0.06	0.08	0.05

Figure.1 SAR and Copeland Ranks

(a)

Objects	Indicators Δ	μ
a	0.5	0.5
b	3	5
c	4	3.5
d	2	4
e	2.5	1

→

(b)

Objects	Rank Δ	Rank μ	SAR Rank
a	5	5	5
b	2	1	1.5
c	1	3	2
d	4	2	3
e	3	4	3.5

↓

(c)

Objects	a	B	c	D	e	Copeland Rank
A	0	-2	-2	-2	-2	-8
B	+2	0	0	+2	+2	+6
C	+2	0	0	0	+2	+4
D	+2	-2	0	0	0	0
E	+2	-2	-2	0	0	-2

→

(d)

b
c
d
e
a

(a) Data matrix. (b) SAR (c) Copeland pair-wise comparison matrix (+1 occurrence of (>), -1 occurrence of (<), 0 otherwise). (d) Final relative rank

Conclusion

One simple method of taking decisions on where to start to minimize the negative impact on the environment is to rank objects (plant, areas, technologies, etc.) according to their released contaminating ability. This work has shown that environmental indicators are correlated and this can be used to understand environmental relation and help in reduction of effort in data collection. The exclusion of correlated environmental indicators will not affect the results of ranking the objects if the ranking was based on comparison indicators, methods such as Copeland, SAR, Utility and desirability. The study applies different ranking methods using some environmental indicators in the GCC area. This work has shown a methodology on how to handle environmental data to reach an environmental decision and how to handle missing data which usually exist in many environmental studies.

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How to cite this article:

Ghanima Al-Sharrah, Yusuf I. Ali, Amir A. Al-Haddad. 2016. Dependent Environmental Indicators and Their Effect of Ranking. *Int.J.Curr.Res.Aca.Rev.*4(4): 51-60.
doi: http://dx.doi.org/10.20546/ijcrar.2016.404.006