Sustainability Assessment of Industrial Systems under Uncertainty: A Fuzzy Logic Based Approach to Short-Term to Midterm Predictions

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The sustainability assessment of industrial systems is always a very challenging task due to the existence of various types of uncertainties that are associated with the available data, assessable information, possessed knowledge, and problem understanding, etc. This paper introduces a fuzzy logic based approach for the effective short- and long-term assessment of industrial sustainability under the restrictions of aleatory and epistemic uncertainties. A comprehensive study on a metal-finishing-centered industrial zone is illustrated to show the efficacy of the introduced methodology.

Introduction

Sustainability refers to a state of harmonious interaction among the economic, environmental, and social aspects of the systems of interest, whereas sustainable development refers to the process of continuous improvements and the path that must be followed in order to achieve an improved state of sustainability. According to Brundtland,[1] developments designed to meet the needs of the present should not compromise the ability of future generations to meet their own needs.

As a major branch of sustainability, industrial sustainability focuses on how to pursue the short- to long-term sustainable development of an industrial system, such as a plant, corporation, geographic region, industrial zone, or beyond, where material and energy efficiencies, waste reduction, safety, and synergies among the systems, etc., are among the major concerns. To develop and implement effective strategies for sustainable development, the first, and the most critical, step is to conduct a sustainability assessment. In addressing the temporal and spatial aspects of an industrial sustainability problem, the effectiveness of the assessment depends largely upon the ability to uncover the complex interrelationships among the entities of the system of study and how to deal with various types of uncertainties that appear in the available technical or nontechnical data, information, and possessed knowledge.

The inherent uncertainties in the data and information needed for a study arise from the incomplete and complex nature of the structure of the industrial system. For example, the multifaceted makeup of the interentity dynamics, dependencies, and interrelationships, the uncertain prospect of forthcoming environmental policies (even in the short term), and the indistinct interrelationship among the triple bottom lines of industrial sustainability (i.e., how the environmental, economic, and societal components of the system effect each other) are frequently (very) uncertain. Moreover, the specific data regarding material or energy consumption, product, waste, or byproduct generation, amount of recycle, and profitability of an individual plant, industry, or zone are often incomplete and imprecise. These uncertainties can also appear in future planning, such as potential modifications to environmental policies, market demand, and supply chain structures, etc., and can be even more difficult to deal with.

According to Parry,[2] uncertainties can be classified into two types: aleatory and epistemic. Aleatory uncertainty refers to the inherent variations associated with the physical system or the environment under consideration, and it is objective and irreversible. By contrast, epistemic uncertainty is carried by the lack of knowledge and/or information, and it is subjective and reducible. The uncertainties encountered in the study of large-scale industrial sustainability problems, as exemplified above, can be either aleatory or epistemic.

A variety of mathematical techniques, and computer and cognitive science based methods, are available for handling uncertainties, such as those utilizing fuzzy logic theory, statistics theory, and artificial intelligence.[3–10] Fuzzy logic based approaches are capable of formulating and manipulating both the aleatory and the epistemic uncertainties.[11–13] Fuzzy logic theory is a mathematical system where rigorous logical mathematics are used to deal with fuzzy information and data that are difficult to compute using conventional mathematics.[14] It supports the use of both qualitative and quantitative data with an outcome of either linguistic or numerical solutions. Furthermore, a fuzzy logic based system can be fine-tuned and improved as more information or knowledge regarding the system becomes available. All these mathematical advantages justify the adoption of fuzzy set theory in methodological study on sustainability assessment.

Our previous work in the area of industrial sustainability has focused on quantified analysis and decision-support capabilities.[15,16] This previous work, as well as other existing works in the area of sustainability, does not address the need for a methodology for sustainability prediction under uncertainty. The few areas that do address this need are less systematic in nature.[15–19] Additionally, the most common method implemented to quantify industrial sustainability is through the use of industrial related metrics.[20,21] This paper will address the aforementioned gaps by introducing a fuzzy logic based industrial sustainability assessment tool for short-term to midterm predictions under uncertainty.

Methodological Framework

There are five major tasks in the development of a sustainability assessment methodology: (1) to identify the sustainability metrics for the industrial problem of study, (2) to select the system variables suitable for metrics evaluation and data collection, (3) to classify and represent uncertainties, (4) to generate a fuzzy rule based knowledge base, and (5) to determine a fuzzy reasoning mechanism.

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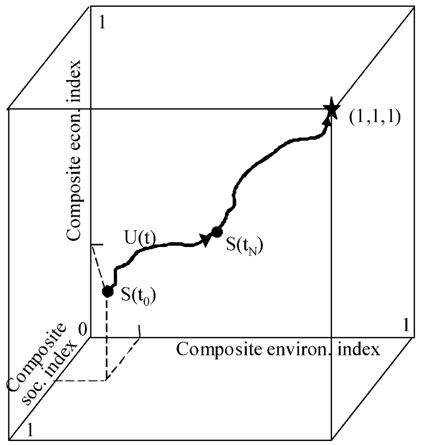

Figure 1. Cube-based sustainability evaluation: Time-variant status change and development path.

Cube-Based Sustainability Status Representation. As stated, a complete sustainability assessment must include the evaluation of the short- to long-term performance of economic, environmental, and social sustainability. Here, we propose to construct a sustainability cube as shown in Figure 1, where the three coordinates represent the composite economic index, the composite environmental index, and the composite social index. Each composite index is set to have a value between 0 (meaning no sustainability) and 1 (meaning complete sustainability). With this representation, the corner coordinate of (0, 0, 0) represents the system's status of no sustainability, while the opposite corner having the coordinate (1, 1, 1) indicates complete sustainability. In the figure, the point, $S(t_0)$, represents the system's overall sustainability status at time t_0, which is determined by the values for each of the triple bottom lines, as marked in the figure. The other point, $S(t_N)$, depicts the overall sustainability status at time t_N. The improvement in sustainability is due to the implementation of a set of strategies, $U(t)$, shown in the figure, where the curve describes a path of sustainable development over time.

For each of the triple bottom lines of sustainability, a variety of sustainability metrics are available for use. For the chemical and allied industry, the most widely utilized sustainability metrics are complied by IChemE[20] and AIChE.[21] These metrics are grouped for assessing economic, environmental, and social sustainability. Each composite index mentioned above is generated by combining the selected indicators in the same sustainability category by assigning different weights; e.g.,

$$S_{\mathrm{j}} = \sum_{i=1}^{N} \alpha_{\mathrm{j},i}\, \tilde{x}_{\mathrm{j},i} \tag{1}$$

where S_{j} = the jth type of composite sustainability index, j = e (economic), v (environmental), or l (social), $\tilde{x}_{\mathrm{j},i}$ = the ith normalized indicator value in the jth composite index, N = the number of indicators selected in the jth sustainability category, and $\alpha_{\mathrm{j},i}$ = the weighting factor between 0 and 1.

Note that each normalized indicator value, $\tilde{x}_{\mathrm{j},i}$, is obtained by either measurement or observation, whereas each coefficient, $\alpha_{\mathrm{j},i}$, is determined by data regression or fine-tuned by the user on the basis of experience with the system and knowing which indicators are more critical to the assessment. The sum of the weighting factors should be 1, in order to ensure that the composite index value is also normalized.

Assessment System Structure. A fuzzy logic based sustainability assessment system is depicted in Figure 2. It is composed of the following functional components: (a) a knowledge base,

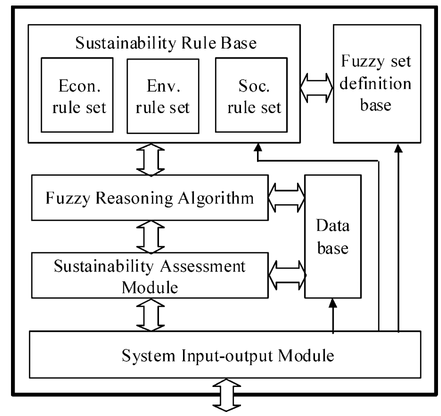

Figure 2. Fuzzy logic based sustainability assessment system.

which consists of three rule sets for each of the triple bottom lines and a fuzzy set definition base that provides quantified information to the rule sets; (b) an inference engine that includes a fuzzy reasoning algorithm and a sustainability assessment module that manages assessment activities; (c) a database that stores the necessary data related to the industrial system under investigation and all other related information; (d) a system input−output module, which accepts the information of the industrial system and all other related data, and outputs the assessment results along with a detailed analysis. Furthermore, it has the capability to accept modifications to the existing rule base as well as the fuzzy sets for knowledge base enhancement.

In the following sections, the fuzzy rule based knowledge base and the influence engine are described in detail.

Fuzzy Logic Based Modeling and Assessment

As stated, the most widely accepted sustainability metrics for the chemical industries are complied by IChemE[20] and AIChE.[21] It is important to note that not all are related to the study of industrial sustainability. Metric selection is usually based on the type of problem under investigation as well as the emphasis of sustainability study. To quantify the selected metrics, different types of system variables are then identified on the basis of the understanding of the industrial system that is to be characterized. Then, many sets of data for the selected system variables should be collected. Note that in executing this task, the following two types of uncertainties will arise: (i) uncertain correlation among variables due to the lack of a deep knowledge about the industrial system and (ii) incompleteness, impreciseness, and insufficiency of the data collected due to the difficulties in data collection. Approaches for knowledge representation through rules, data handling, and fuzzy reasoning are introduced below.

Knowledge Base Structure. In fuzzy logic, uncertainty is expressed as fuzzy numbers and intervals. Intervals are needed when the number values are not known with certainty but about which bounds can be established. Fuzzy numbers are uncertainty numbers for which, in addition to knowing a range of possible values, one can say that some values are more possible than others. Fuzzy inputs can be obtained by subjective assignments, objective consensus, and inference from measurement errors, etc. One unique feature about fuzzy mathematics is that when data are inconsistent, the analyst can find and emphasize regions of consonance and use a clustering approach to define "similarity" between intervals. The inputs to the knowledge base are the values for estimating basic indicators of sustainability, which are provided by the user. The inputs are then combined, through the use of fuzzy sets that are specified by individual IF−THEN rules to produce a composite output indicator, also determined by the user. The benefits of using such an approach are that (i) the user has the freedom to select the indicators most relevant to their assessment needs and (ii) the knowledge base can be updated and adjusted to fit the specific needs and expertise of the system as more information is available, thus resulting in a flexible and accommodating industrial sustainability assessment framework.

The knowledge base contains three rule sets, namely, sets R_e, R_v, and R_l, for assessing economic, environmental, and social sustainability, respectively. Each set may contain a different number of fuzzy rules, $R_j = \{R_j^i | i=1,2,...,N_j^M\}$, where j is the index of sustainability category ("e" for economic, "v" for environmental, and "*l*" for social); N_j^M represents the total number of rules in rule set R_j. Each rule takes the structure below:

R_j^i:

$$\begin{aligned} &\text{IF} \qquad \{x_{j,k} = A_{j,k}^i | k = 1, 2, ..., N_j\} \\ &\text{THEN} \quad S_j^i = \sum_{k=1}^{N_j} a_{j,k}^i \tilde{x}_{j,k} \end{aligned} \tag{2}$$

where $x_{j,k}$ = the kth indictor in the jth sustainability category, $\tilde{x}_{j,k}$ = the kth indictor (normalized) in the jth sustainability category, $A_{j,k}^i$ = the fuzzy set defined for indicator $x_{j,k}$ in rule R_j^i, $a_{j,k}^i$ = the coefficient associated with normalized indicator $\tilde{x}_{j,k}$ in rule R_j^i, N_j = the total number of indicators included in rule R_j^i to evaluate sustainability, S_j^i = the jth sustainability category derived by rule R_j^i, and j = the sustainability index category (e, economic; v, environmental; *l*, social).

Note that since the THEN part of this type of rule is a numerical expression, it provides a quantitative conclusion, which is desirable in most cases for sustainability assessment. Due to the potential for a quantitative evaluation, this type of rule is advantageous over the type of rule where the THEN part is purely linguistic, which can only perform qualitative evaluations. Note that to use the rule type in eq 2, both experience and experimental data (which most likely will be incomplete, imprecise, and/or uncertain) must be available.

Fuzzy Reasoning and Confidence Level. To conduct each category of sustainability assessment, the MIN−MAX algorithm[12] is adopted. Mathematically, this algorithm can be expressed as follows:

$$\mu_j(x) = \max\{\min\{\mu_i(x_{j,k}) | k = 1, 2,..., N_j\}\}, \quad i = 1, 2,..., M \tag{3}$$

where $\mu_i(x_{j,k})$ = the fuzzy membership value for the indicator $x_{j,k}$ in the ith rule in the jth sustainability category, $\mu_j(x)$ = the derived membership value after the MIN−MAX operation on the rules in the jth sustainability category, and x = a general representation of variables $x_{j,k}$.

The above algorithm is in fact implemented in two steps. In the first step, each rule in a specific rule set has its condition part (i.e., the IF part) evaluated for its truthfulness in the following way:

$$\tau_i = \min\{\mu_i(x_{j,k}) | k = 1, 2, ..., N_j\}, \quad i = 1, 2,..., M \tag{4}$$

This operation on each rule gives rise to the least truthfulness (i.e., MIN) of the conditions in the rule. Thus, it is the most conservative evaluation of the usefulness of the rule in assessment. Therefore, this conservative evaluation, τ_i, can be considered as the confidence level if rule R^i is selected for sustainability evaluation.

For a rule set of M rules, the above operation gives rise to M τ_i values. In the succeeding step, the following MAX operation is performed:

$$\tau_j = \max\{\tau_1, \tau_2, ..., \tau_M\}, \quad j = 1, 2,..., \text{or } M \tag{5}$$

The above operation identifies the largest truth value and, in turn, the rule that is to be activated. For instance, if τ_k has the MAX value among the M τ_i's, then the kth rule is selected for use. Furthermore, if the rule set being evaluated by this algorithm is for the evaluation of economic sustainability, then τ_k is the confidence level of the assessment in this sustainability category.

In summary, the MIN−MAX operation should be implemented for each of the three sustainability categories. It will identify one rule from each of the three rule sets for sustainability evaluation and provide the most conservative confidence level.

Fuzzy Sets Creation. The effectiveness of the rule-based assessment largely depends on the fuzzy sets defined for the sustainability indicators. There are two methods that could be implemented for the generation of membership functions: subjective or data-driven. The subjective approach relies on the collection of experience and knowledge from a team of experts in the area of study, where experimental data are very incomplete and imprecise. The team, after determining which fuzzy sets are to be included (i.e., LOW, MODERATE, and HIGH, etc.), analyzes each variable and determines the shape of each fuzzy set. The approach could be highly subjective, but the result could be satisfactory due to the involvement of experts. Note that as new information becomes available and more knowledge is gained, the fuzzy sets can be modified and updated.

The data-driven approach, on the other hand, clusters experimental data into subregions, which can then be linguistically interpreted, e.g., LOW and HIGH. If necessary, the subregions may also be further divided, thus resulting in a higher level of linguistic interpretation, until a satisfactory model is generated.[23] Fuzzy sets can take on a variety of shapes, and many data-driven approaches exist for generating membership functions, including those simply based on predetermined high and low boundary values.[23] Furthermore, taking this idea a step further, Kainuma et al. utilize an approach that also takes data clustering or density into account when generating necessary fuzzy sets.[24,25] The trapezoidal membership functions, for example, can be expressed in a very general form:

$$A(x) = \begin{cases} \dfrac{1}{2(x_2 - x_1)}x + \dfrac{x_2 - 2x_1}{2(x_2 - x_1)} & \text{if } 2x_1 - x_2 \le x < x_2 \\ 1 & \text{if } x_2 \le x < x_3 \\ -\dfrac{1}{2(x_4 - x_3)}x + \dfrac{2x_4 - x_3}{2(x_4 - x_3)} & \text{if } x_3 \le x < 2x_4 - x_3 \\ 0 & \text{if } x < 2x_1 - x_2 \text{ or } 2x_4 - x_3 \le x \end{cases} \tag{6}$$

where x_1, x_2, x_3, and x_4 are the minimum, the first quartile, the third quartile, and the maximum of the data set for variable x.

To further clarify the approach utilized by Kainuma et al.,[25] a method generating a fuzzy membership function based on available data is introduced, which is related to the case studies presented later in this paper. Figure 3a displays the historical environmental sustainability indicator data (hazardous solid waste generated per unit value added, $x_{v,4}$, as a function of total raw materials used per pound of product, $x_{v,1}$), which has been

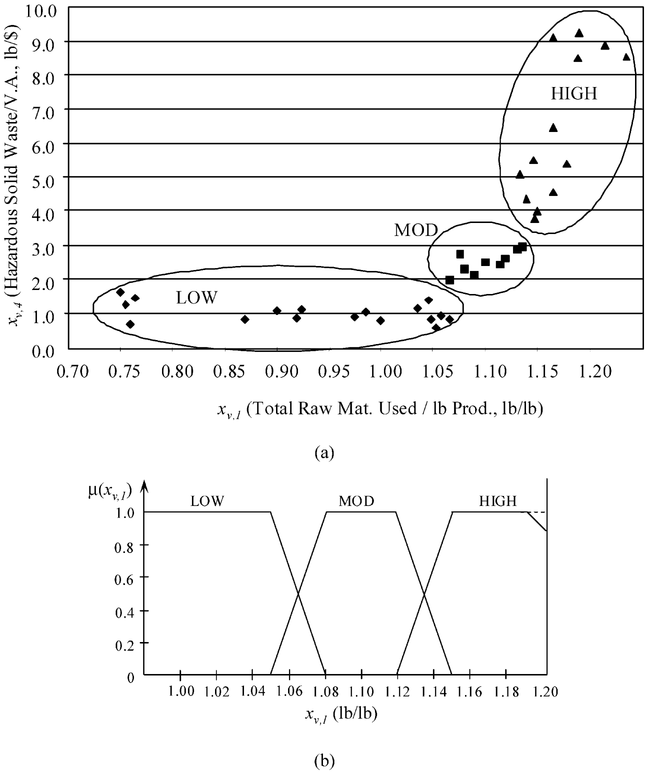

Figure 3. Example of fuzzy clustering of the data about total raw materials used and hazardous solid waste data: (a) data clustering; (b) fuzzy set definition.

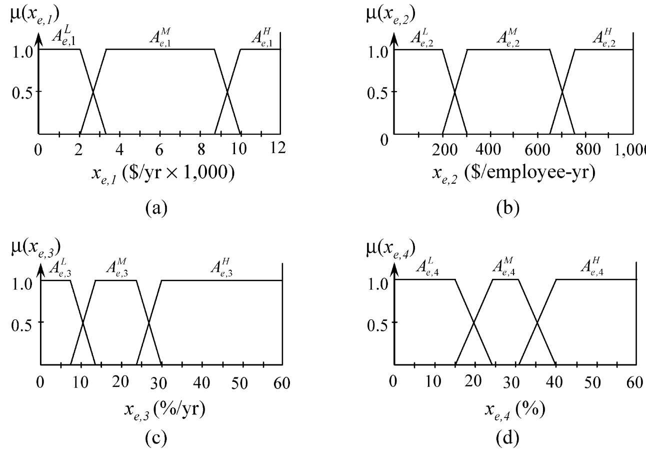

Figure 4. Definition of fuzzy sets for four economic sustainability indicators: value added ($x_{e,1}$); (b) gross margin per direct employee ($x_{e,2}$); (c) return on average capital employed ($x_{e,3}$); (d) taxes paid as a percentage of net income before tax ($x_{e,4}$).

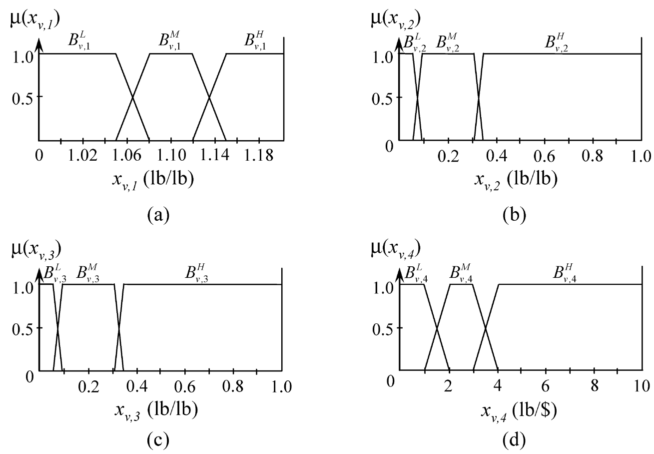

Figure 5. Definition of fuzzy sets for four environmental sustainability indicators: (a) total raw materials used per pound of product produced ($x_{v,1}$); (b) fraction of raw materials recycled within a company ($x_{v,2}$); (c) fraction of raw materials recycled from consumers ($x_{v,3}$); (d) hazardous solid waste per unit value added ($x_{v,4}$).

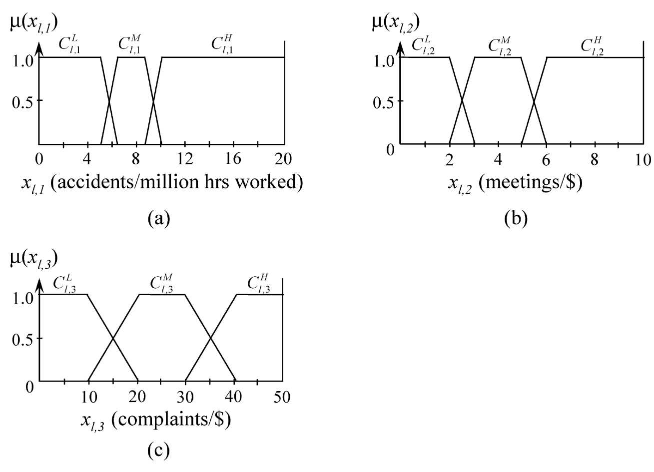

Figure 6. Definition of fuzzy sets for three social sustainability indicators: (a) lost time accident frequency ($x_{l,1}$); (b) number of stakeholder meetings per unit value added ($x_{l,2}$); (c) number of complaints per unit value added ($x_{l,3}$).

obtained for an industrial zone composed of multiple industries and multiple plants. The data essentially represent a form of plant efficiency. In other words, the lower the hazardous solid waste generated by those plants, the lower the required raw material input into their processes, typically due to a higher level of plant efficiency techniques (e.g., in plant recycle capabilities). Conversely, plants requiring a higher level of raw material input into their processes generate a larger amount of hazardous solid waste, due to the fact that their plant efficiency is lacking.

As shown in Figure 3a, the data can be clustered on the basis of the density of data points within a given region of the data scatter. For this example, three linguistic subregions have been identified for $x_{v,1}$, LOW, MODERATE, and HIGH. Utilizing the method given in eq 6, the fuzzy sets for the environmental sustainability variable, the total raw materials used per pound of product ($x_{v,1}$), are given in Figure 3b. Analyzing the fuzzy sets in Figure 3b, it can be seen that the HIGH membership function is equal to 1.0 for values of $x_{v1} = 1.15-1.19$; however, the membership function for values greater than 1.19 changes. This could be indicative of the fact that the HIGH subregion could be further divided and an additional linguistic value introduced. For the purposes of our case studies, however, it was assumed that the HIGH membership function is equal to 1.0 for values of $x_{v,1} > 1.15$, as shown with the dotted line in Figure 3b. This same approach is used to generate all of the membership functions for each of the economic, environmental, and social variables, Figures 4−6, respectively.

Overall Sustainability Assessment. As shown in Figure 1, each of the composite sustainability indices, S_e, S_v, and S_l, are normalized to have a value between 0 and 1. It is highly desirable that the overall sustainability level, S, is also normalized. According to Figure 1, the following formula can be used to derive a normalized S value:

$$S = \frac{1}{\sqrt{3}}||(S_e, S_v, S_l)|| \tag{7}$$

Assessment Confidence Level. Let R_e^i, R_v^j, and R_l^k respectively represent the three rules selected in the economic, environmental, and social sustainability rule sets, and τ_e^i, τ_v^j, and τ_l^k correspond to the identified corresponding membership values. As stated earlier, these values are taken as the conservative confidence levels for the assessment of each sustainability category. Note that the confidence level of the overall sustainability assessment can be derived using the MIN operation in the following way.

$$C_S = \min\{\tau_e^i, \tau_v^j, \tau_l^k\} \tag{8}$$

Again, this is a conservative confidence level, which should be acceptable in most assessment cases.

Case Study

The introduced methodology has been used to study a number of industrial sustainability problems. In this section, an industrial zone's sustainable development problem is selected for illustrating the efficacy of the methodology. The focus of the study is on the assessment of the short-term to midterm impact of different development strategies on an industrial zone.

Problem Description. The industrial zone under study is sketched in Figure 7. The industrial zone consists of two chemical suppliers to the electroplating plants (H_1 and H_2), two electroplating shops (H_3 and H_4), two end users, in this case, two original equipment manufacturers (OEM) for the automotive industry (H_5 and H_6), and a regional wastewater treatment facility (WWTF). The WWTF is charged with cleaning the waste streams, from each of the component plants, to a level that is environmentally satisfactory for discharge into the local river and environment. Both case 1 and case 2, which represent two zone production plan options, evaluate the sustainable development within this region.

Sustainability Metrics Selection. For the case study described above, a subset of 11 of IChemE's sustainable development progress metrics[20] have been selected.

Table 1. Economic Sustainability: Evaluation of Rule Set and Rule Selection[a]

variable:	$x_{e,1}$	$x_{e,2}$	$x_{e,3}$	$x_{e,4}$		
input data:	10.0	690.0	25.0	32.0	MIN operation	MAX operation
rule no.	$\mu_i(x_{e,1})$	$\mu_i(x_{e,2})$	$\mu_i(x_{e,3})$	$\mu_i(x_{e,4})$	$\tau_{e,i}$	τ_e
R_e^1	0.00	0.00	0.00	0.15	0.00	0.63
R_e^2	0.00	0.00	0.00	0.00	0.00	
R_e^3	0.00	0.00	0.00	0.85	0.00	
R_e^4	0.00	0.00	0.78	0.15	0.00	
R_e^5	0.00	0.00	0.22	0.15	0.00	
R_e^6	0.00	0.63	0.00	0.15	0.00	
R_e^7	0.00	0.37	0.00	0.15	0.00	
R_e^8	0.00	0.00	0.00	0.15	0.00	
R_e^9	1.00	0.00	0.00	0.15	0.00	
R_e^{10}	0.00	0.63	0.78	n/a	0.00	
R_e^{11}	0.00	0.63	n/a	0.85	0.00	
R_e^{12}	0.00	n/a	0.78	0.85	0.00	
R_e^{13}	n/a	0.63	0.78	0.85	0.63	
R_e^{14}	1.00	0.37	0.22	0.85	0.22	
R_e^{15}	1.00	0.37	0.22	0.15	0.15	
R_e^{16}	1.00	0.37	0.00	0.00	0.00	
R_e^{17}	1.00	0.37	0.78	0.00	0.00	
R_e^{18}	1.00	0.00	0.22	0.00	0.00	
R_e^{19}	1.00	0.63	0.22	0.00	0.00	
R_e^{20}	0.00	0.37	0.22	0.00	0.00	
R_e^{21}	0.00	0.37	0.22	0.00	0.00	
R_e^{22}	1.00	0.37	0.22	0.00	0.00	

[a] Note: "n/a" indicates that the relevant indicator is not counted in the condition part of that rule.

(a) For economic sustainability assessment, the selected indicators are as follows: (1) value added ($x_{e,1}$), which is defined as the difference of the sales and the total cost of goods, raw materials (including energy), and services purchased; (2) gross margin per direct employee ($x_{e,2}$), which is defined as the ratio of the difference between the sales and all the variable costs and the number of direct employees; (3) return on the average capital employed ($x_{e,3}$); (4) taxes paid as a percentage of net income before tax ($x_{e,4}$).

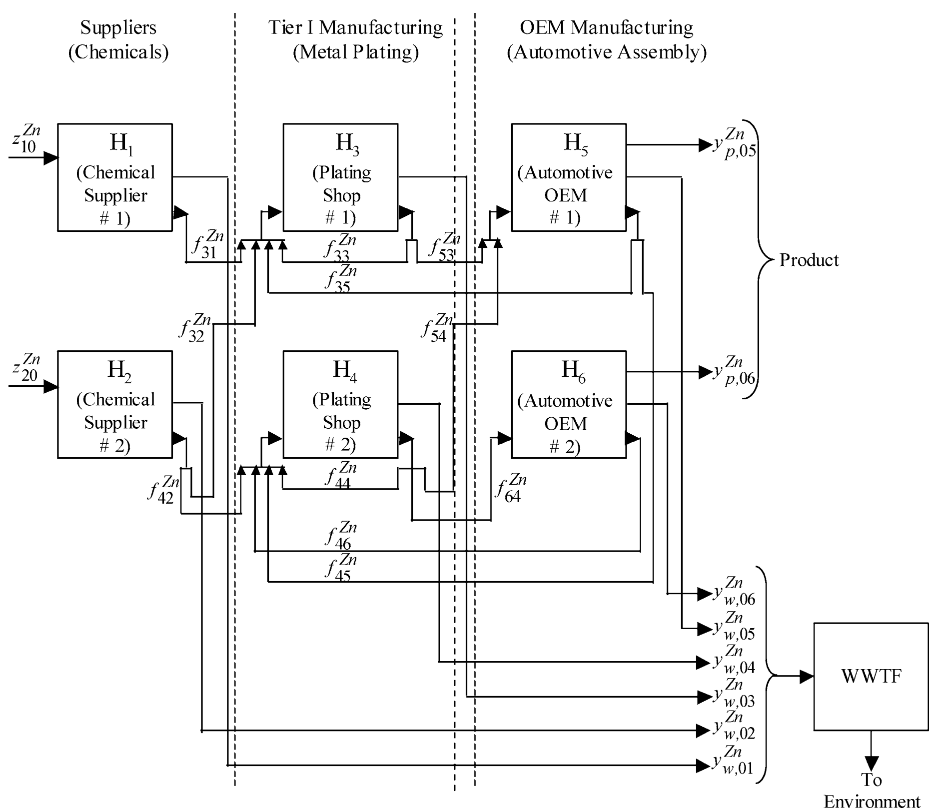

Figure 7. Surface finishing industrial region.

(b) In the environmental sustainability category, four indicators are selected: (1) total raw materials used per pound of product produced ($x_{v,1}$), which is the ratio between the pounds of raw material used and the pounds of product produced; (2) the fraction of raw materials recycled within a company ($x_{v,2}$); (3) the fraction of raw materials recycled from consumers ($x_{v,3}$); (4) the hazardous solid waste per unit value added ($x_{v,4}$).

(c) In the social sustainability assessment category, the suitable indicators are as follows: (1) lost time accident frequency ($x_{l,1}$); (2) the number of stakeholder meetings per unit value added ($x_{l,2}$); (3) the number of complaints per unit value added ($x_{l,3}$).

Rule Sets and Fuzzy Sets. As stated, the knowledge base contains three rule sets, namely, sets R_e, R_v, and R_l, for assessing economic, environmental, and social sustainability, respectively. For this case study, the knowledge base has 61 rules, including 22 rules in set R_e, 22 rules in set R_v, and 17 rules in set R_l.[26] While the uniform rule structure has already been given in eq 2, the first rule in each of the three rules sets are listed as follows as examples.

R_e^1:

$$\begin{aligned} &\text{IF} \quad x_{e,1} = A_{e,1}^{L},\ x_{e,2} = A_{e,2}^{L},\ x_{e,3} = A_{e,3}^{L},\ \text{and}\ x_{e,4} = A_{e,4}^{H} \\ &\text{THEN} \quad S_e = \sum_{i=1}^{4} \alpha_{e,i}^{R_e^1} \tilde{x}_{e,i} \end{aligned} \tag{9}$$

where the fuzzy sets $A_{e,1}^{L}$, $A_{e,2}^{L}$, $A_{e,3}^{L}$, and $A_{e,4}^{H}$ for indicators $x_{e,1}$, $x_{e,2}$, $x_{e,3}$, and $x_{e,4}$ in this rule are defined in Figure 4a–d. Note that in Figure 4, a total of 12 fuzzy sets are defined. These fuzzy sets are used in different ways by the other 21 rules in the economic sustainability rule set.

R_v^1:

$$\begin{aligned} &\text{IF} \quad x_{v,1} = B_{v,1}^{H},\ x_{v,2} = B_{v,2}^{H},\ x_{v,3} = B_{v,3}^{H},\ \text{and}\ x_{v,4} = B_{v,4}^{H} \\ &\text{THEN} \quad S_v = \sum_{i=1}^{4} \beta_{v,i}^{R_v^1} \tilde{x}_{v,i} \end{aligned} \tag{10}$$

where the fuzzy sets $B_{v,1}^{H}$, $B_{v,2}^{L}$, $B_{v,3}^{L}$, and $B_{v,4}^{H}$ for indicators $x_{v,1}$, $x_{v,2}$, $x_{v,3}$, and $x_{v,4}$ in this rule are defined in Figure 5a–d. Note that Figure 5 also gives the definitions for 12 fuzzy sets. These fuzzy sets are used in different ways by the remaining 21 rules in the environmental sustainability rule set.

R_l^1:

$$\begin{aligned} &\text{IF} \quad x_{l,1} = C_{l,1}^{H},\ x_{l,2} = C_{l,2}^{L},\ \text{and}\ x_{l,3} = C_{l,3}^{H} \\ &\text{THEN} \quad S_l = \sum_{i=1}^{3} \gamma_{l,i}^{R_l^1} \tilde{x}_{l,i} \end{aligned} \tag{11}$$

where the fuzzy sets $C_{l,1}^{H}$, $C_{l,2}^{L}$, and $C_{l,3}^{H}$ for indicators $x_{l,1}$, $x_{l,2}$, and $x_{l,3}$ in this rule are defined in Figure 6a–c. Note that Figure 6 contains nine fuzzy sets. These fuzzy sets are used in different ways by the additional 16 rules in the social sustainability rule set.

Also note that the coefficients in the above three rules, $\alpha_{e,i}^{R_e^1}$, $\beta_{v,i}^{R_v^1}$, and $\gamma_{l,i}^{R_l^1}$, are obtained through data regression.

Evaluation of Current Sustainability Status. The current sustainability status, $S(0)$, of the industrial zone can be readily evaluated, which is reflected by the triple-bottom-line status, $S_e(0)$, $S_v(0)$, and $S_l(0)$, according to eq 7. To derive the values of $S_e(0)$, $S_v(0)$, and $S_l(0)$, the assessment system in Figure 2 requires sets of information about the zone operation. In this case, the needed information is the data required for quantifying four economic indicators, $x_{e,i}$ ($i = 1, 2, ..., 4$), four environmental indicators, $x_{v,i}$ ($i = 1, 2, ..., 4$), and three social indicators, $x_{l,i}$ ($i = 1, 2, 3$), as well as the boundary values of each indicator (i.e., $x_{e,i}^{max}$, $x_{e,i}^{min}$, $x_{v,i}^{max}$, $x_{v,i}^{min}$, $x_{l,i}^{max}$, and $x_{l,i}^{min}$), so that the indicator variables can be normalized to $\tilde{x}_{e,i}$, $\tilde{x}_{v,i}$, and $\tilde{x}_{l,i}$.

According to the methodology, the assessment is based on the rules to be activated in the three rule sets. Taking the economic sustainability rule set as an example, one rule should be activated from a total of 22 rules through performing the MIN–MAX operation on all the rules. Table 1 provides the details of the results after the operation. As shown, the data for variables $x_{e,k}$ ($k = 1, 2, ..., 4$) are input by the user. Then, the membership function values for the condition part of each rule, $\mu_i(x_{e,k})$ ($i = 1, 2, ..., 22$; $k = 1, 2, ..., 4$) are all listed, based on the fuzzy sets involved. Note that the fuzzy sets have been fully given in Figure 4a–d. The MIN operation gives rise to $\tau_{e,1}, \tau_{e,2}, ..., \tau_{e,22}$ in Table 1. The MAX operation identifies that $\tau_{e,13}$ has the largest value (0.63). Therefore, rule R_e^{13} is activated.

R_e^{13}:

$$\begin{aligned} &\text{IF} \quad x_{e,2} = A_{e,2}^{M},\ x_{e,3} = A_{e,3}^{M},\ \text{and}\ x_{e,4} = A_{e,4}^{M} \\ &\text{THEN} \quad S_e = 0.1\tilde{x}_{e,1} + 0.3\tilde{x}_{e,2} + 0.3\tilde{x}_{e,3} + 0.3\tilde{x}_{e,4} \end{aligned} \tag{12}$$

The rule application for the economic sustainability quantification generates the results in the top section of Table 2. As shown, the dimensional input data for $x_{e,k}$ ($k = 1, 2, ..., 4$) are first normalized (i.e., $\tilde{x}_{e,k}$, $k = 1, 2, ..., 4$, in Table 2). The quantified value for economic sustainability, S_e from eq 12, is calculated to be 0.57. The confidence level for this evaluation is 0.63, which is equivalent to the result of the MIN–MAX operations discussed above (from Table 1).

Following the same evaluation procedure as that for the economic sustainability assessment, the activated rules in the environmental rule set and the social rule set are found to be

R_v^8:

$$\begin{aligned} &\text{IF} \quad x_{v,1} = B_{v,1}^{L},\ x_{v,2} = B_{v,2}^{L},\ x_{v,3} = B_{v,3}^{L},\ \text{and}\ x_{v,4} = B_{v,4}^{L} \\ &\text{THEN} \quad S_v = 0.15\tilde{x}_{v,1} + 0.35\tilde{x}_{v,2} + 0.35\tilde{x}_{v,3} + 0.15\tilde{x}_{v,4} \end{aligned} \tag{13}$$

R_l^3:

$$\begin{aligned} &\text{IF} \quad x_{l,1} = C_{l,1}^{H},\ x_{l,2} = C_{l,2}^{H},\ \text{and}\ x_{l,3} = C_{l,3}^{H} \\ &\text{THEN} \quad S_l = 0.30\tilde{x}_{l,1} + 0.35\tilde{x}_{l,2} + 0.35\tilde{x}_{l,3} \end{aligned} \tag{14}$$

Using these rules, the quantified values for environmental and social sustainability are 0.15 and 0.34, respectively. In addition, the confidence values resulting from the respective MIN–MAX operations are calculated as 0.46 and 0.80 and are clearly provided in Table 2. Using eqs 7 and 8, the value for overall sustainability along with the confidence level for the whole industrial zone problem can be readily derived as 0.39 and 0.46, respectively, which are also shown in Table 2.

Analysis and Sustainability Improvement Plan Development. The above evaluation can provide some valuable insight information. It is clear that the existing industrial network is economic focused and is lacking in the areas of environmental and social sustainability practices, as the values of S_v and S_l are much smaller than S_e. Furthermore, by taking the environmental and social dimensional input data from Table 2, along with the respective fuzzy sets for each indicator in

Table 2. Sustainability Assessment of the System at Year 0

ECON indicator	input data (dimensional)	normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	categorized sustainability ($S_e(0)$)	categorized confidence (C_e)
$x_{e,1}$	10.0	0.83	0.10	0.57	0.63
$x_{e,2}$	690.0	0.69	0.30		
$x_{e,3}$	25.0	0.25	0.30		
$x_{e,4}$	32.0	0.68	0.30		
ENV indicator	**input data (dimensional)**	**normalized value ($\tilde{x}_{v,i}$)**	**$\beta_{v,i}$**	**categorized sustainability ($S_v(0)$)**	**categorized confidence (C_v)**
$x_{v,1}$	1.06	0.12	0.15	0.15	0.46
$x_{v,2}$	0.08	0.08	0.35		
$x_{v,3}$	0.02	0.02	0.35		
$x_{v,4}$	3.70	0.63	0.15		
SOC indicator	**input data (dimensional)**	**normalized value ($\tilde{x}_{l,i}$)**	**$\gamma_{l,i}$**	**categorized sustainability ($S_l(0)$)**	**categorized confidence (C_l)**
$x_{l,1}$	11.4	0.43	0.30	0.34	0.80
$x_{l,2}$	2.2	0.22	0.35		
$x_{l,3}$	30.6	0.39	0.35		
overall sustainability	**overall confidence**				
$S(0) = 0.39$	$C(0) = 0.46$				

Figures 5 and 6, we can dig deeper into where improvements can be made at the industrial zone level, to impact environmental and social sustainability. Specifically from an environmental point of view, the area of most concern is the fraction of raw materials recycled from consumers, $x_{v,3}$ (100% inclusion in fuzzy set "LOW"), followed by the hazardous solid waste per unit value added, $x_{v,4}$ (68% inclusion in fuzzy set "HIGH"), then the fraction of raw materials recycled within a company, $x_{v,2}$ (54% inclusion in fuzzy set "MOD"), and finally the total raw materials used per pound of product produced, $x_{v,1}$ (67% inclusion in fuzzy set "LOW"). Using the same approach for social sustainability, the area of highest concern is lost time accident frequency, $x_{l,1}$ (100% inclusion in fuzzy set "HIGH"), followed by the number of stakeholder meetings per unit value added, $x_{l,2}$ (80% inclusion in fuzzy set "LOW"), and finally the number of complaints per unit value added, $x_{l,3}$ (85% inclusion in fuzzy set "MOD").

The results of this analysis are useful in identifying areas that require improvement and provide aid in future zone planning decisions for sustainability improvement. For this case, the strategy for sustainable development must follow the form where economic sustainability will achieve a steady

Table 3. Sustainability Improvement Plans A and B

improvement focus	current (year 0)	short term (year 3)	midterm (year 6)
Plan A			
main plan for environmental sustainability improvement			
fraction of raw materials recycled within a company ($x_{v,2}$)	0.08	0.22	0.30
fraction of raw materials recycled from consumers ($x_{v,3}$)	0.02	0.15	0.25
hazardous solid waste per unit value added ($x_{v,4}$)	3.7	1.5	1.4
main plan for social sustainability improvement			
lost time accident frequency ($x_{l,1}$)	11.4	7.8	6.2
number of complaints per unit value added ($x_{l,3}$)	30.6	20	12
Plan B			
main plan for environmental sustainability improvement			
fraction of raw materials recycled within a company ($x_{v,2}$)	0.08	0.15	0.35
fraction of raw materials recycled from consumers ($x_{v,3}$)	0.02	0.10	0.32
hazardous solid waste per unit value added ($x_{v,4}$)	3.7	3.2	1.2
main plan for social sustainability improvement			
lost time accident frequency ($x_{l,1}$)	11.4	9.8	3.0
number of stakeholder meetings per unit value added ($x_{l,2}$)	2.2	2.2	5.4
number of complaints per unit value added ($x_{l,3}$)	30.6	25	6

Table 4. Short-Term Sustainability Assessment after Implementing Plan A

ECON indicator	input data (dimensional)	normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	categorized sustainability ($S_e(3)$)	categorized confidence (C_e)
$x_{e,1}$	10.2	0.85	0.35	0.68	0.60
$x_{e,2}$	725.0	0.73	0.30		
$x_{e,3}$	29.0	0.29	0.20		
$x_{e,4}$	32.0	0.68	0.15		
ENV indicator	**input data (dimensional)**	**normalized value ($\tilde{x}_{v,i}$)**	**$\beta_{v,i}$**	**categorized sustainability ($S_v(3)$)**	**categorized confidence (C_v)**
$x_{v,1}$	1.02	0.15	0.10	0.38	0.50
$x_{v,2}$	0.22	0.22	0.30		
$x_{v,3}$	0.15	0.15	0.30		
$x_{v,4}$	1.50	0.85	0.30		
SOC indicator	**input data (dimensional)**	**normalized value ($\tilde{x}_{l,i}$)**	**$\gamma_{l,i}$**	**categorized sustainability ($S_l(3)$)**	**categorized confidence (C_l)**
$x_{l,1}$	7.8	0.61	0.35	0.50	1.00
$x_{l,2}$	2.5	0.25	0.30		
$x_{l,3}$	20.0	0.60	0.35		
overall sustainability	**overall confidence**				
$S(3) = 0.53$	$C(3) = 0.50$				

Table 5. Midterm Sustainability Assessment after Implementing Plan A

ECON indicator	input data (dimensional)	normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	categorized sustainability ($S_e(6)$)	categorized confidence (C_e)
$x_{e,1}$	10.9	0.91	0.35	0.71	0.82
$x_{e,2}$	735.0	0.74	0.30		
$x_{e,3}$	33.0	0.33	0.20		
$x_{e,4}$	28.0	0.72	0.15		
ENV indicator	input data (dimensional)	normalized value ($\tilde{x}_{v,i}$)	$\beta_{v,i}$	categorized sustainability ($S_v(6)$)	categorized confidence (C_v)
$x_{v,1}$	1.02	0.15	0.10	0.44	0.40
$x_{v,2}$	0.30	0.30	0.30		
$x_{v,3}$	0.25	0.25	0.30		
$x_{v,4}$	1.40	0.86	0.30		
SOC indicator	input data (dimensional)	normalized value ($\tilde{x}_{l,i}$)	$\gamma_{l,i}$	categorized sustainability ($S_l(6)$)	categorized confidence (C_l)
$x_{l,1}$	6.2	0.69	0.35	0.57	0.78
$x_{l,2}$	3.0	0.30	0.35		
$x_{l,3}$	12.0	0.76	0.30		
overall sustainability	overall confidence				
$S(6) = 0.58$	$C(6) = 0.40$				

Table 6. Short-Term Sustainability Assessment after Implementing Plan B

ECON indicatos	input data (dimensional)	normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	categorized sustainability ($S_e(3)$)	categorized confidence (C_e)
$x_{e,1}$	9.6	0.80	0.10	0.58	0.31
$x_{e,2}$	720.0	0.72	0.30		
$x_{e,3}$	25.0	0.25	0.30		
$x_{e,4}$	30.0	0.70	0.30		
ENV indicator	input data (dimensional)	normalized value ($\tilde{x}_{v,i}$)	$\beta_{v,i}$	categorized sustainability ($S_v(3)$)	categorized confidence(C_v)
$x_{v,1}$	1.07	0.11	0.10	0.29	0.73
$x_{v,2}$	0.15	0.15	0.30		
$x_{v,3}$	0.10	0.10	0.30		
$x_{v,4}$	3.20	0.68	0.30		
SOC indicator	input data (dimensional)	normalized value ($\tilde{x}_{l,i}$)	$\gamma_{l,i}$	categorized sustainability ($S_l(3)$)	categorized confidence (C_l)
$x_{l,1}$	9.8	0.51	0.30	0.41	0.74
$x_{l,2}$	2.2	0.22	0.35		
$x_{l,3}$	25.0	0.50	0.35		
overall sustainability	overall confidence				
$S(3) = 0.44$	$C(3) = 0.31$				

Table 7. Midterm Sustainability Assessment after Implementing Plan B

ECON indicator	regular data (dimensional)	normalized value ($\tilde{x}_{e,i}$)	$\alpha_{e,i}$	categorized sustainability ($S_e(6)$)	categorized confidence (C_e)
$x_{e,1}$	10.5	0.88	0.35	0.70	0.75
$x_{e,2}$	730.0	0.73	0.30		
$x_{e,3}$	30.0	0.30	0.20		
$x_{e,4}$	26.0	0.74	0.15		
ENV indicator	regular data (dimensional)	normalized value ($\tilde{x}_{v,i}$)	$\beta_{v,i}$	categorized sustainability ($S_v(6)$)	categorized confidence (C_v)
$x_{v,1}$	1.02	0.15	0.15	0.53	0.68
$x_{v,2}$	0.35	0.35	0.25		
$x_{v,3}$	0.32	0.32	0.20		
$x_{v,4}$	1.20	0.88	0.40		
SOC indicator	regular data (dimensional)	normalized value ($\tilde{x}_{l,i}$)	$\gamma_{l,i}$	categorized sustainability ($S_l(6)$)	categorized confidence (C_l)
$x_{l,1}$	3.0	0.85	0.40	0.77	0.58
$x_{l,2}$	5.4	0.54	0.30		
$x_{l,3}$	6.0	0.88	0.30		
overall sustainability	overall confidence				
$S(6) = 0.67$	$C(6) = 0.58$				

improvement, while the environmental and social sustainability aspects will be significantly enhanced. To achieve this outcome, two improvement plans are proposed in Table 3 (where the data provided are the dimensional input data for each scenario over time), plan A (short term, to be achieved in the first 3 years) and plan B (midterm, to be achieved in the second 3 year span). The two plans are very similar, with the exception of one additional improvement area for social sustainability in plan B; however, the stagewise goals of the two plans are quite different. Plan A emphasizes its major efforts on the first 3 years and more passively maintains the industrial zone without any major investment over the course of years 4−6. On the contrary, plan B focuses on incorporating small improvements throughout the first 3 years and will make major investment over the period of years 4−6. Note that the two plans are developed on the basis of different business development strategies; this is not discussed here as it is outside the scope of this work. The next section looks

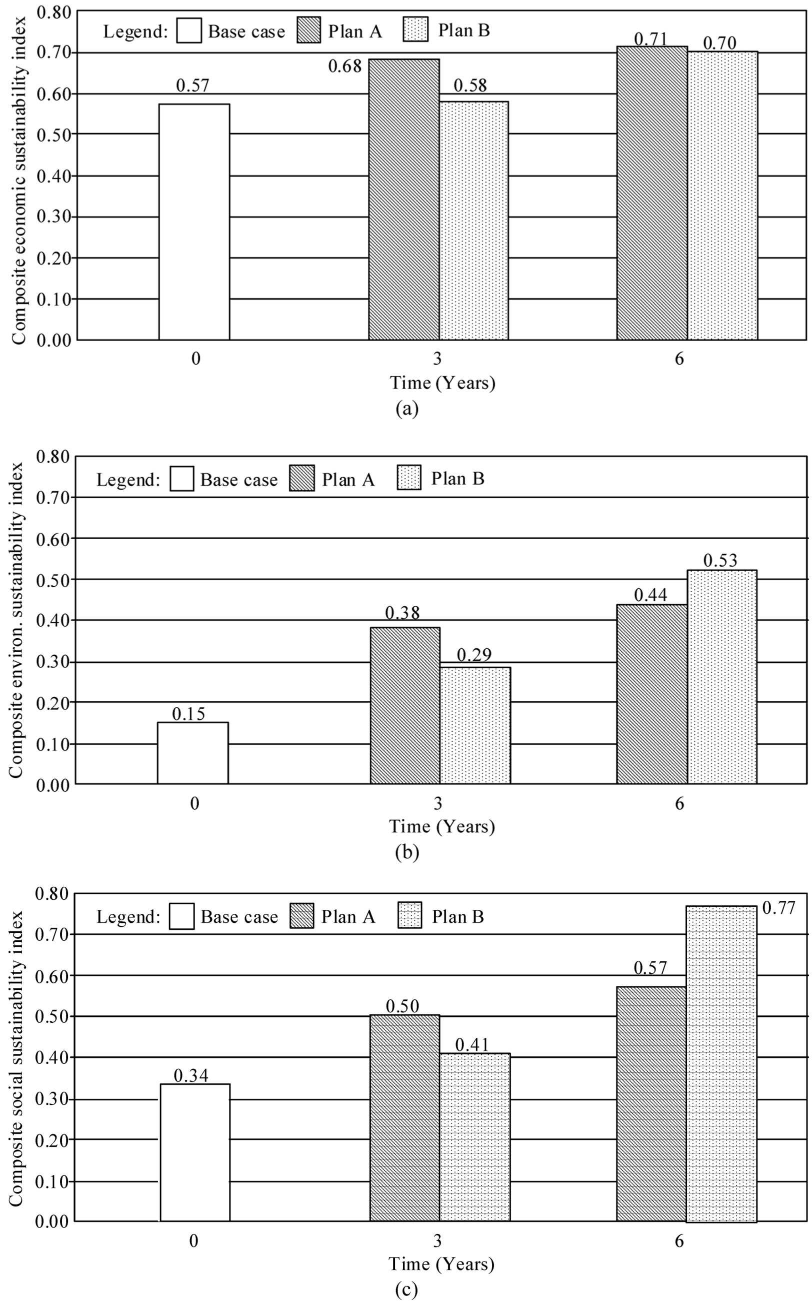

Figure 8. Case-based sustainability status comparison: (a) economic sustainability performance; (b) environmental sustainability performance; (c) social sustainability performance.

to evaluate the sustainability improvement for each plan over the time span of 6 years.

Short-Term and Midterm Assessment of Plan A. The introduced methodology can be readily applied to assess the proposed plans for sustainability improvement. Tables 4 and 5 provide, respectively, the detailed assessment on the zone's short-term and midterm sustainable development status by implementing plan A. The tables show that the economic sustainability is steadily improved over the 6 year period (see $S_e(0) = 0.57$, $S_e(3) = 0.68$, and $S_e(6) = 0.71$). The environmental and social sustainability, on the other hand, are each improved significantly (see $S_v(0) = 0.15$, $S_v(3) = 0.38$, and $S_v(6) = 0.44$; and $S_l(0) = 0.34$, $S_l(3) = 0.50$, and $S_l(6) = 0.57$). Overall, the sustainability level of the industrial zone can be raised from a value of 0.39 (current) to 0.53 (in 3 years) and then to 0.58 (after 6 years). Note that this methodology can also provide a piece of additional, and important, information, i.e., the confidence level for the assessment of each of the triple bottom lines of sustainability as well as overall sustainability, which is also shown in Tables 4 and 5. The confidence levels are quite different at each time interval, which is mainly due to the confidence in the quality of the available data as well as the data interpretation in different sustainability assessment categories. It should be pointed out that the confidence data reflect the most conservative assessment, which shows the minimum confidence that can be guaranteed for the assessment.

Short-Term and Midterm Assessment of Plan B. As stated earlier, plan B has its feature of emphasizing its improvement focus in the second stage (i.e., in years 4−6) due to other business considerations. Tables 6 and 7 list all of the details for the short-term and midterm assessments. It is shown that economic sustainability is steadily improved (see $S_e(0) = 0.57$, $S_e(3) = 0.58$, and $S_e(6) = 0.70$). However, the environmental and social sustainability are each improved significantly (see $S_v(0) = 0.15$, $S_v(3) = 0.29$, and $S_v(6) = 0.53$; and $S_l(0) = 0.34$, $S_l(3) = 0.41$, and $S_l(6) = 0.77$). Overall, the sustainability level

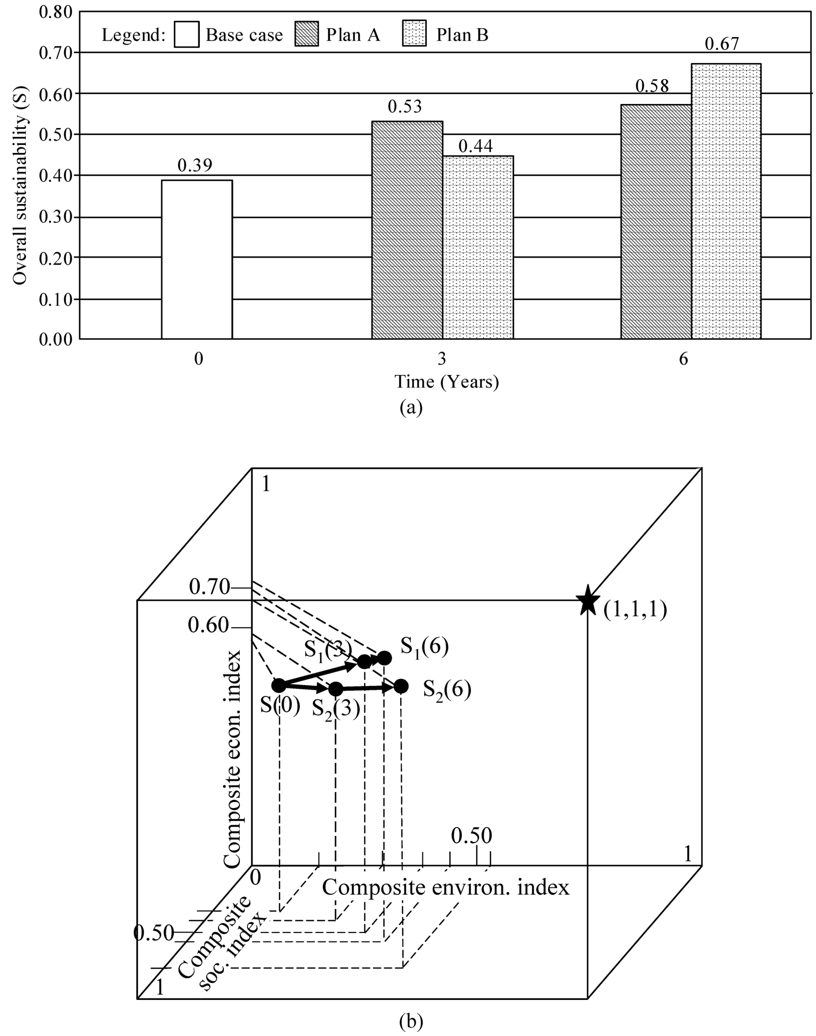

Figure 9. Overall system sustainability performance comparison: bar-chart description; (b) cube-based description.

of the industrial zone can be raised from 0.39 (current) to 0.44 (in 3 years) and then to 0.67 (thereafter 6 years). It is clear that this plan's focus on the midterm improvement has been achieved. The conservative confidence information is also provided in Tables 6 and 7.

Comparison of Development Plans. The goals of each plan's developments are the same, i.e., to ensure the steady development of the zone's economic sustainability but, at the same time, to significantly improve the environmental and social sustainability in a number of target areas. The plan-based evaluations described all show that these two plans are feasible. As a comparison, Figure 8 depicts the categorized sustainability improvements achieved by the plans over two different time frames (short-term and midterm). Plan A makes a major impact on the improvement in the short term, whereas plan B emphasizes a major improvement in the midterm. This improvement difference is eventually reflected in the overall sustainability change. As shown in Figure 9a, plan A shows a better sustainability performance over plan B in the short term; however, for midterm performance, plan B is clearly better. Figure 9b depicts the two sustainable development paths as a result of implementing the two different plans. If short-term performance is the primary concern, plan A would be more desirable. However, if the zone's planner focuses on a midterm performance goal, plan B would be more advantageous.

Concluding Remarks

One of the major challenges in a sustainability assessment is how to appropriately deal with unavoidable uncertainties that are associated with the data, information, and knowledge. This paper has introduced a fuzzy logic based assessment methodology that can effectively represent and manipulate aleatory and epistemic uncertainties, which are the major forms of uncertainties encountered in the study of large-scale industrial sustainability problems. The methodology is general, systematic, and easy to apply. It is particularly useful for the assessment of strategic plans for future sustainability improvement. The case study on a metal-finishing-centered industrial zone problem has clearly shown the efficacy of the methodology.

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