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A Comprehensive and Integrated Stochastic-Fuzzy Method for Sustainability Assessment in the Malaysian Food Manufacturing Industry

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Abstract: Manufacturing activities carry significant burdens for all three dimensions of sustainability, i.e., environment, economy and society. However, most of the available sustainability assessment methods for manufacturing are based on environmental concerns only. Moreover, it is hard to find a sustainability assessment method that considers both stochastic and fuzzy uncertainties concurrently and a comprehensive set of weighted and applicable indicators. Thus, the main purpose of this paper was to develop and test an integrated sustainability assessment method that included both stochastic and fuzzy uncertainties. Both quantitative and qualitative, and weighted sustainability indicators for the Malaysian food manufacturing industry needed to be considered, with reliable assessment results. In order to achieve the objective, the Monte Carlo simulation and fuzzy logic approaches were employed. An overall unit-less sustainability index was calculated to evaluate the current sustainability level. This method was demonstrated using a real-world case study of a Malaysian food manufacturing company. The results highlighted and traced the company-wide major low and high performing areas for all three dimensions of sustainability. The results unveiled that the case company could improve its sustainability performance more effectively by decreasing the amount of air emissions, polluted wastewater, etc., and improving the working conditions. This would enable the practitioners and decision-makers to allocate resources accordingly and more efficiently. Finally, the developed method was validated and the implications and conclusions of the research were presented.

Keywords: fuzzy logic; food industry; Monte Carlo simulation; sustainability assessment; sustainable manufacturing; Triple-bottom line

1. Introduction

Sustainable manufacturing concept and practice are becoming increasingly a topic of significant interest globally. The need for sustainable manufacturing has become crucial due to the fact that manufacturing activities consume a large amount of energy and natural resources [1,2], produce considerable emissions to air and land and deteriorate the earth's carrying capacity [3], while having significant implications for the society and economy. More specifically, the expanding food manufacturing industry due to the rapid growth in world population and changing lifestyles, results in the consumption of global resources at a faster pace [4]. The food sector contributes more than 25% of greenhouse gas (GHG) emissions alone [5,6] and is responsible for a large share of water withdrawal [7,8]. Moreover, food manufacturing also produces a significant amount of solid waste, wastewater, etc., [9]. In addition, the food manufacturing industry normally provides high-calorie and unfavorable nutritions in processed food which have potential harmful effects on eating and drinking behaviors [10]. In short, food manufacturing (processing and packaging) is critical from a sustainability viewpoint, especially in recent times when the world is facing global issues of environmental degradation, fragile and volatile economy and food security and safety.

To respond to this situation, sustainable food manufacturing has become a major concern and priority. In order to improve sustainability performance and green perception, assessment is an essential process [11–14]. An assessment and reassessment of how food manufacturing activities are undertaken is necessary to take on the challenges of sustainability while mitigating water usage, energy consumption and negative social and economic impacts. However, although food manufacturing contributes significantly to sustainability related burdens, it has not been given due attention by previous research from sustainability assessment and improvement viewpoints, especially in developing countries [15]. The major focus of sustainability related research has been on metal manufacturing, building and construction, chemical processing, etc.

The focus of previous sustainability assessment methods and studies in manufacturing remained mainly on environmental concerns alone [16–19]. However, the triple-bottom line (TBL) concept of sustainability [20,21] requires manufacturing industries to consider all three aspects (environment, economy and society) of sustainability comprehensively. Most of the time, sustainability assessment efforts in food manufacturing were limited to life cycle assessment or energy analysis [8,22–24]. Very few studies were based on the TBL concept. Recently, Ali et al. [25] tried to include other dimensions of sustainability for food manufacturing; however, their research was limited to environmental and economic impacts only, while the social aspect was overlooked.

Currently available sustainability assessment methods face various challenges, which resultantly hinder their practical application. For example, most of the sustainability assessment methods are based on quantitative indicators only, whereas qualitative indicators are overlooked because of various reasons [26,27]. Moreover, the unavailability of applicable and measurable indicators dissuades practitioners to assess sustainability performance. Instead of having generic and overall indicators, applicable and weighted sustainability indicators need to be used for specific industries [15,28–30]. This would give more standardized, precise and comparable sustainability evaluation [31–35].

Optimal sustainability related decisions can only be made when both types of fuzzy and stochastic uncertainties are included in one assessment method. Fuzziness (imprecise information) and randomness (stochastic variability) are the two main sources of uncertainties in the real world, which are also associated with sustainability assessment problems. However, overall, many sustainability assessment methods have simply overlooked both fuzzy and stochastic uncertainties. Even in a recent study [36], uncertainties associated with the data for sustainability assessment were ignored. Among other relevant methods, life cycle sustainability assessment (LCSA) by United Nations Environment Programme (UNEP)/Society of Environmental Toxicology and Chemistry (SETAC) [37] is an important method for TBL based assessment. However, LCSA is an impact assessment method, just like life cycle assessment (LCA) [38]. LCSA is based on general guidelines and there is a need to develop a comprehensive and weighted set of indicators. Additionally, from economic and social viewpoints, the impact categories and how to measure them have yet to be agreed upon [38]. Moreover, the concept of stochastic and fuzzy uncertainties is also missing in LCSA.

The above mentioned research gaps and discussion highlight the need for the development of a TBL-based comprehensive and integrated sustainability performance assessment method that integrates both stochastic and fuzzy uncertainties, while considering weighted and applicable sustainability indicators. Thus, this novel study provides contributions in various aspects. Theoretically, it would answer the research question of how to integrate stochastic and fuzzy uncertainties in a sustainability assessment method. It would also demonstrate how to include and analyze qualitative and quantitative indicators concurrently. This would help to further improve the capabilities of sustainability assessment methods. Practically, by demonstrating the application of this method in the Malaysian food manufacturing industry, it is expected to increase sustainability assessment efforts in a developing country like Malaysia, and may eventually improve its sustainability performance. Currently, the Malaysian food manufacturing industry lags behind in applying sustainability practices in its operations [39,40].

To achieve the objective of developing an integrated sustainability assessment method, the Monte Carlo simulation and fuzzy logic approaches were used simultaneously. Fuzzy logic was used for qualitative indicators because it is suitable to address linguistic variables when evaluating sustainability. However, fuzzy logic is unable to address the dynamic and probabilistic nature of quantitative variables. Thus, Monte Carlo simulation was utilized for quantitative indicators to solve this problem. The Crystal Ball software for Monte Carlo simulation and the Fuzzy Logic toolbox of Matlab (R2015b) were used. In order to show the applicability of the developed method, a case study was done in the Malaysian food manufacturing industry. Real data were collected from a case company and the developed method was applied to assess its sustainability performance. After this, the method was validated for its robustness and the results obtained were analyzed and discussed.

The rest of this article is arranged as follows. Section 2 presents the background and some general concepts, and the developed method is described in Section 3. The application of the method in a case study along with the results are presented in Section 4. Section 5 provides an analysis and discussion. Validation of the method is presented in Section 6. Section 7 outlines various implications for practitioners and researchers, and important conclusions are provided in Section 8.

2. Background and General Concepts

As discussed earlier, the main objective of this article was to develop and test a comprehensive and integrated sustainability performance assessment method that is based on stochastic and fuzzy approaches. Thus, this section briefly describes the concept of sustainability assessment along with Monte Carlo simulation and fuzzy logic.

2.1. Sustainability Assessment

In simple words, sustainability assessment can be defined as the process that evaluates the implications of an initiative on sustainability [41] and directs decision-making towards sustainability [20,42]. It is being increasingly seen as an important tool to aid in the shift towards sustainability [15,43–45]. The objective of sustainability assessment is to ensure that products, processes, industries, activities, etc., make an optimal contribution to sustainable development [46]. In this respect, sustainability assessment would ensure and improve the sustainability performance of manufacturing activities.

In order to perform a sustainability assessment, various indicators [47,48] are utilized to give values to the dimensions of sustainability [49]. Moreover, sustainability assessment can be undertaken at different levels and boundaries. From a manufacturing viewpoint, the plant/factory level assessment (including all manufacturing processes) gains more importance as it directly leads to energy uptake and emission, etc., and helps in internal decision-making for improving sustainability performance more effectively [15,50]. Currently, sustainability assessment based on the TBL concept is quite challenging when all three dimensions of sustainability are considered in a comprehensive way [51].

2.2. Monte Carlo Simulation

One of the most straightforward and important stochastic modeling techniques is Monte Carlo simulation. It is a computational method for generating probability distributions of variables that depend on other variables or parameters represented as probability distributions [52]. Theoretically, this method is grounded on an entirely random process and it has been proven statistically that with enough sampling iterations, one can accurately generate output realization distributions [53,54]. In this research, the Monte Carlo method was used because of its several advantages over other techniques (probabilistic programming, etc.). For example, it is simple to be implemented and no mathematical equation is needed to describe the behavior of a system.

In general, the Monte Carlo simulation involves various steps. Firstly, the selection of a range or distribution (e.g. uniform, lognormal, triangular, etc.) for a variable is done. In the second step, the samples are generated from the range or distribution specified earlier. Next, based on the mean or variance, the uncertainty is analyzed. After a sufficiently large number of simulations, the distribution function of the output can be determined. Various studies found that 1000 simulations are sufficient for proper analysis and for delivering a stable output [54–56]. More information on the theory of Monte Carlo simulation and how it works can be found in the literature [52,57,58]. The Monte Carlo approach has been used in other research areas. For example, it was used for water quality related risk assessment [59], air quality and risk assessment [53], health related risk modeling [60,61], etc. However, its application in sustainability assessment was normally limited to environmental analysis or sometimes to cost analysis only [62–64].

2.3. Fuzzy Logic

Fuzzy logic, as a scientific tool, helps to address deficiencies inherent in binary logic and handle uncertainties in real-life situations. It has the capabilities of human logical thinking, which make it as a natural choice or tool for sustainability assessment [65]. Moreover, fuzzy logic can handle various number of qualitative indicators. This makes the sustainability assessment more comprehensive. Due to these advantages and characteristics, fuzzy logic was used in this research to address fuzzy uncertainties.

In fuzzy logic, the truth of a statement is supposed to be a matter of degree, and linguistic variables (e.g. very poor, poor, average, good and very good) are used to address the degree of imprecision. A fuzzy system contains a rule base and a reasoning algorithm, which are used to process fuzzy input values to a crisp output value. Knowledge is represented by IF–THEN linguistic rules. Using the procedure developed by Mamdani and Assilian, three steps are taken to create a rule-based fuzzy system: (1) fuzzification—using membership functions to graphically describe a situation; (2) rule evaluation—application of fuzzy rules by the combination of two sub-processes: inference and composition based on given fuzzy rules; and (3) defuzzification—obtaining crisp or actual results [53,65]. Fuzzy logic has been used in various sustainability assessment studies [65–67]. However, considering sustainability as a fuzzy concept only is not adequate. Sustainability related decision-making using either the fuzzy or stochastic approach solely may lead to potential shortcomings and sub-optimal decisions. The integrated usage of stochastic and fuzzy approaches is hard to be found for sustainability assessment purposes, especially in manufacturing. Thus, the proposed method is aimed to capture stochastic as well as fuzzy uncertainties in sustainability assessment. This is elaborated more in the next section.

3. The Proposed Method

The basic modeling components of the proposed method are shown in Figure 1. Overall, in order to capture stochastic and fuzzy uncertainties, the method was based on both types of quantitative and qualitative indicators. The quantitative indicators (environmental, economic and social indicators) were treated as stochastic variables, whereas the qualitative indicators (social indicators) were analyzed as fuzzy variables. For simplicity purposes, the method was divided into two sub-systems (quantitative indicators based sub-system and qualitative indicators based sub-system). The method used the fuzzy logic approach for the qualitative indicators based sub-system. The quantitative indicators based sub-system was analyzed based on Monte Carlo simulation first, and then followed by fuzzy logic. The TBL based total sustainability index was grounded on the weighted contribution of each sub-system.

At the outset, using Monte Carlo simulation requires input information to be specified; however, in many real-world applications, the available information is imprecise and scarcely accessible. In such situations, when there are very limited sample data for an uncertain parameter, the triangular distribution is used, where it is based on knowledge of the minimum, maximum and most likely modal values [68–70]. Since in this study, the possible ranges of industry data were used for the indicators, it seemed reasonable to use the triangular distribution. The minimum, most likely and maximum values were used to infer the lower bounds, modes and upper bounds of the triangular distributions.

The quantitative indicators were directly measured based on their measuring units, whereas the qualitative indicators were recorded based on linguistic measures, using a Likert scale from 1 to 5 [71]. The qualitative indicators were processed by using fuzzy models or Fuzzy Inference Systems (FISs). The triangular membership function was used in the fuzzy models because it is the simplest and most commonly used membership function owing to its ability to be adapted into various assessments [65,72,73]. The Mamdani method was used as the fuzzy model and the centroid method was utilized as the defuzzification approach. The Mamdani-type FIS was used because it is widely accepted and provides more consistent results [74,75]. Moreover, the selection of the centroid defuzzification method was based on its superior results and steady-state performance [76,77]. Briefly, the proposed sustainability assessment method is presented below as a set of steps:

Step 1: As the first step, the goal and scope of the study were defined and the system boundary was specified. The goal and scope were identified at the earliest stage of the evaluation process. In this research, the goal was to develop a method for assessing the sustainability performance of a plant/factory in the Malaysian food manufacturing industry. The scope included the system boundary (either cradle-to-gate, cradle-to-grave, gate-to-grave or gate-to-gate). The extent of the system boundary depended on the goal of the study.

Step 2: This stage was related to the identification and selection of applicable sustainability indicators and their relative weights from the viewpoint of the Malaysian food manufacturing industry. Normally, previous sustainability-related research used a limited number of indicators for ease and simplicity purposes. In contrast, this research was based on a comprehensive set of 57 sustainability indicators. The weighted and applicable indicators that were specifically developed for the Malaysian food manufacturing industry were used. These indicators were first extracted from the literature and then refined and finalized for this specific industry using the Delphi method while engaging various experts from academia, research center and industry. These indicators were reported in [78]. The weights of the indicators were calculated based on the applicability scores recommended by the experts [78]. In addition, a positive or negative sign (+ or −) was assigned to each indicator based on its direction of impact on sustainability performance. In other words, if the objective is to increase an indicator's value, its sign is positive (+); otherwise, its sign is negative (−).

Step 3: The selection of the food manufacturing company was primarily based on the size of the company, and its willingness to participate and share the related data for analysis purposes. As the aim was to develop an applicable and practicable method, Small and Medium Enterprises (SMEs) were chosen for initial demonstration. This was done because SMEs generally find it difficult to cope with emerging challenges due to their financial, technical and other constraints. Thus, in a sense, it could help food manufacturing SMEs in Malaysia.

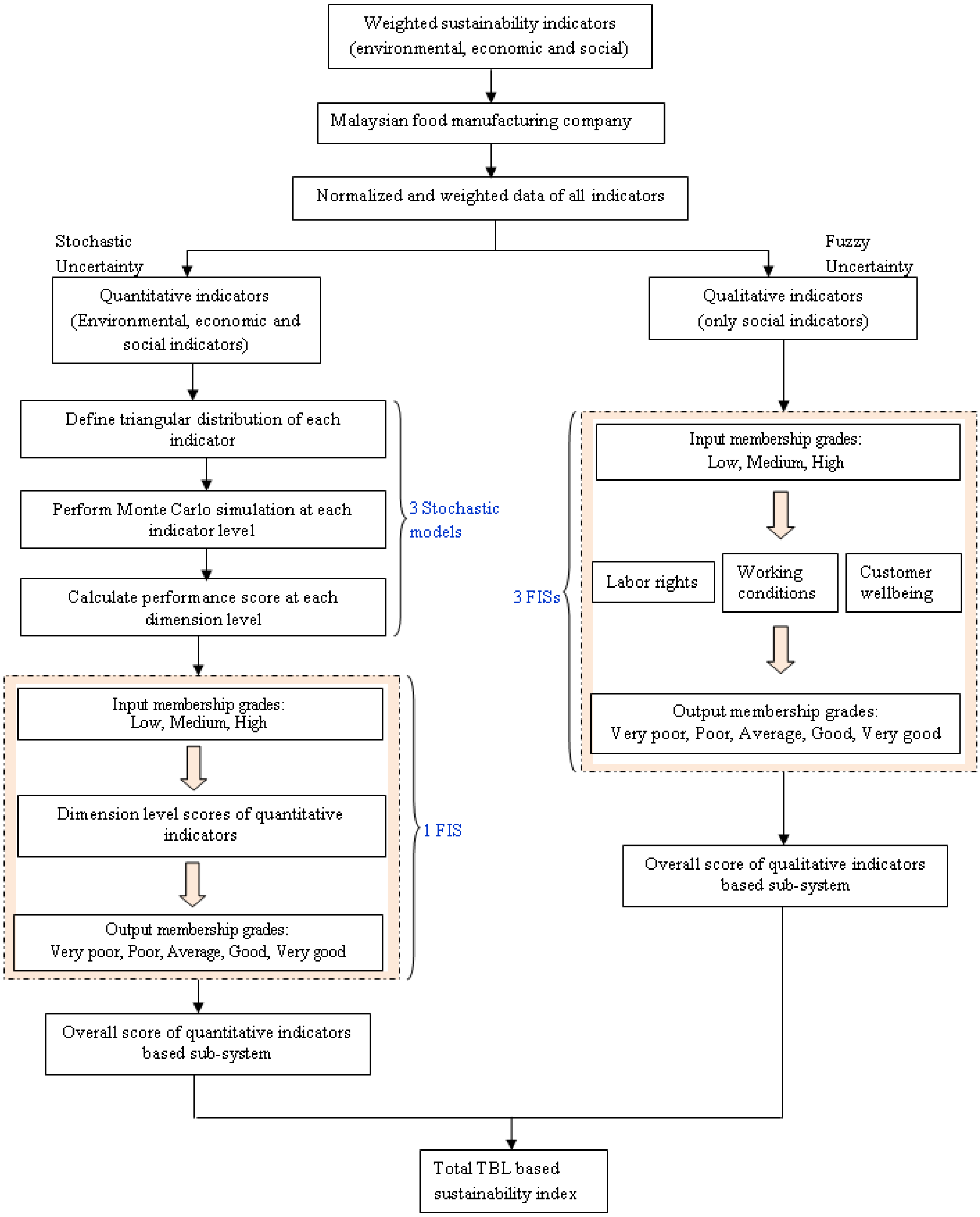


Figure 1. Flow chart of the proposed integrated stochastic-fuzzy sustainability assessment method.

Step 4: The data were collected from the case study company and they were normalized and weighted for each indicator. Due to different measuring units of different indicators, they could not be processed directly. The data were normalized from 0 to 1 to solve this problem. Two formulas were used; one for indicators with a positive sign (+) and another for indicators with a negative sign (−) [79]. Equation (1) shows the calculation to normalize scores for positive indicators, and Equation (2) is for negative indicators. The normalized score $\widetilde{x}_{mn}$ was calculated using c_n^+ as the maximum score and c_n^- as the minimum score among the three-point data (f_{mn}^1, f_{mn}^2, f_{mn}^3). As depicted in Equation (3), the normalized score was simply multiplied by the weight (w_n) of the respective indicator to get the normalized weighted score ($\widetilde{c}_{mn}$) of that indicator:

$$\widetilde{x}_{mn} = \left(\frac{f^1_{mn}}{c^+_n}, \frac{f^2_{mn}}{c^+_n}, \frac{f^3_{mn}}{c^+_n}\right) \quad (1)$$

$$\widetilde{x}_{mn} = \left(\frac{c^-_n}{f^3_{mn}}, \frac{c^-_n}{f^2_{mn}}, \frac{c^-_n}{f^1_{mn}}\right) \quad (2)$$

$$\widetilde{c}_{mn} = w_n.\widetilde{x}_{mn} \quad (3)$$

For qualitative indicators, in order to get a single real value ($P(\widetilde{m})$) based on three fuzzy estimates, the graded mean integration representation method [80] was used. The formula is given in Equation (4):

$$P(\widetilde{m}) = \frac{1}{6}(a + 4b + c) \quad (4)$$

Step 5: This step was about the assessment of the qualitative indicators based sub-system. There were nine social indicators in the qualitative indicators based sub-system under three aspect categories (labor rights, working conditions and customer wellbeing). The fuzzy logic approach was used, and thus, three FISs (one for each aspect category) were designed for the qualitative indicators. In order to develop the FISs, three degrees of triangular membership functions were used for the input variables; low (L), medium (M) and high (H). Three degrees were employed, because they were simple and also commonly used in engineering and management problems. As for the output, five degrees of triangular membership functions were used; very poor (VP), poor (P), average (A), good (G) and very good (VG). Five degrees were proposed to obtain a more accurate result with lower complexity. The fuzzy membership grades (degrees) for the input and output variables are presented in Tables 1 and 2, respectively. Equation (5) was used to calculate the number of rules required in each FIS:

$$R = n^v \quad (5)$$

where n represents the number of fuzzy membership grades for input variables, v is the number of input variables (indicators) for each aspect category and R stands for the number of rules needed. The labor rights category was based on three indicators, thus, the rule base comprised 27 rules. The second aspect category (working conditions) consisted of only two indicators, thus, nine rules were used. There were four indicators in the customer wellbeing category, and thus, it required 81 rules. All the rules were connected by using the 'AND' operator. The defuzzified value generated by each FIS was used as the score of each aspect category. These scores were summed up to obtain the overall score for the qualitative indicators based sub-system.

Table 1. Fuzzy membership grades for input variables.

Number	Membership Grades			Description
1	0.0	0.0	0.5	Low
2	0.0	0.5	1.0	Medium
3	0.5	1.0	1.0	High

Table 2. Fuzzy membership grades for output variables.

Number	Membership Grades			Description
1	0.0	0.0	0.25	Very poor
2	0.0	0.25	0.50	Poor
3	0.25	0.50	0.75	Average
4	0.50	0.75	1.0	Good
5	0.75	1.0	1.0	Very good

Step 6: The quantitative indicators based sub-system was analyzed using two approaches: firstly, the Monte Carlo simulation was used to address the stochastic uncertainties and then fuzzy logic to cope with the directions of impact of sustainability dimensions. The values of the quantitative indicators were stochastic, and therefore, it was important to simulate their performance. The three-point data were used to represent the triangular distributions. Simulation was performed 1000 times at each indicator level (19 environmental, 14 economic and 15 social indicators) [54–56]. The dimension level performance was calculated by adding/subtracting (based on the impact direction of an indicator) the average simulated scores of all quantitative indicators in each dimension. In this way, the environmental, economic and social (with stochastic indicators) dimensions were assigned a score based on the stochastic analysis.

The dimension level scores obtained through stochastic simulation were used to develop another FIS in order to get the overall score for the quantitative indicators based sub-system. Actually, the dimension level scores based on Monte Carlo simulation were not having the same direction of impact on sustainability performance. Since there are more indicators with a negative sign in the environmental and economic dimensions, a lower score means better performance for these two dimensions of sustainability. However, in the case of the social dimension, a higher score is better. Thus, in order to solve this problem, another FIS was designed. The same number of triangular membership functions with the same range, as mentioned in Step 5 were defined for the variables. There were three variables (three sustainability dimensions), which required 27 rules to describe the problem fully. However, because of the direction of impact of the environmental and economic dimensions, different membership grades (Table 3) were designed for these two dimensions.

Step 7: The overall TBL-based sustainability index was calculated based on the scores received in the previous two steps. The weighted scores of both the sub-systems (qualitative indicators based and quantitative indicators based sub-systems) were summed up to get the total TBL sustainability index of the overall system. Based on this final sustainability index, the food manufacturing company's sustainability performance could be categorized into one of the five levels given in Table 4.

Table 3. Fuzzy membership grades for environmental and economic dimensions.

Number	Membership Grades	Description
1	0.0 0.0 0.5	High
2	0.0 0.5 1.0	Medium
3	0.5 1.0 1.0	Low

Table 4. Overall triple-bottom line (TBL) based sustainability performance levels.

Number	Index Range	Description
1	0.0–0.19	Very poor
2	0.2–0.39	Poor
3	0.4–0.59	Average
4	0.6–0.79	Good
5	0.8–1.00	Very good

4. Case Study

In order to demonstrate the usefulness of the developed method, it was tested through a case study in a Malaysian food manufacturing company. The company's name is not disclosed for anonymity purposes, and thus, is simply denoted as "ABC Company". It is an independent small sized food manufacturing factory, located in Penang, Malaysia. The company is famous for frozen Halal meatballs and it was established in 1997. The production factory consists of various sophisticated food manufacturing machineries, while strictly observing the Halal and hygienic food manufacturing practices. The meatballs are made up of beef mince mixed with beef fat, flour and herbs and spices consisting mainly of salt, pepper, sodium compound, onion and garlic. This mixture is formed into small ball-shaped patties and the patties are fully cooked in boiling water. The finished products are pre-cooled and then blast-frozen or stored in a cold room. The meatballs are packed in small packages first that are further put into reusable crates or cartons based on customer demand.

The system boundary for sustainability assessment was gate-to-gate in this case study. The gate-to-gate boundary starts from the receiving of raw materials and includes manufacturing and packaging processes in a factory [15]. This boundary was selected to perform a detailed analysis of the food factory and to support internal decision-making. Thus, other life cycle phases, such as preprocessing, usage, etc., were not included.

4.1. Data Collection

Since the system boundary was gate-to-gate in this research, input and output data were collected only for manufacturing and packaging activities which were happening inside the food factory. Data related to other life cycle phases, such as pre-processing, transportation, usage, etc., were not collected as they were beyond the scope of this study. The company provided monthly, weekly or daily basis data and these were converted to 'per product' data for simplicity and comparison purposes. Data used in this study were gathered through site visits and face-to-face interviews with the production manager. As mentioned earlier, data for the quantitative indicators were measured based on their measuring units, whereas the qualitative indicators were recorded in terms of linguistic measures which were based on a Likert scale from 1 to 5 [71]. These linguistic measures and their corresponding values are given in Table 5.

Table 5. Linguistic variables and their values for qualitative indicators.

Number	Linguistic Variable	Measuring Scale
1	Very low (VL)	1
2	Low (L)	2
3	Medium (M)	3
4	High (H)	4
5	Very high (VH)	5

4.2. Normalization and Weighting of the Data

Normalization was done using Equations (1) and (2). An indicator's weight was multiplied with its normalized value to obtain its normalized weighted value (Equation (3)). Tables 6–8 show the data for the quantitative indicators and Table 9 presents the qualitative indicators' data for the case company. For the qualitative indic±ators, a single real value ($P(\widetilde{m})$) was calculated using Equation (4).

Table 6. Environmental inventory data.

Aspect Category	Indicators	Measuring Units	Indicators' ID	±	Indicators' Scores			C_n^+	C_n^-	Normalized Scores			Indicators' Weights	Normalized Weighted Scores		
					Min.	Most Likely	Max.			Min.	Most Likely	Max.		Min.	Most Likely	Max.
Material used	Raw materials	g	Env-1	–	1010	1015	1020	n/a	1010	0.990	0.995	1	0.0620	0.0614	0.0617	0.0620
	Primary packaging materials (cans, containers, bottles, etc.)	g	Env-2	–	4	5	6	n/a	4	0.667	0.8	1	0.0571	0.0381	0.0457	0.0571
	Secondary packaging materials (cardboards, boxes, etc.)	g	Env-3	–	25	28	30	n/a	25	0.833	0.893	1	0.0571	0.0476	0.0510	0.0571
	Biodegradable packaging materials	g	Env-4	+	10	14	20	20	n/a	0.5	0.7	1	0.0441	0.0220	0.0308	0.0441
Energy used	Fuel (diesel, petrol, etc.)	L	Env-5	–	0	0	0	n/a	0	0	0	0	0.0522	0	0	0
	Natural gas	Kg	Env-6	–	0.8	0.85	0.9	n/a	0.8	0.889	0.941	1	0.0441	0.0392	0.0415	0.0441
	Electricity	kWh	Env-7	–	0.04	0.043	0.048	n/a	0.04	0.833	0.930	1	0.0636	0.0530	0.0592	0.0636
Water used	Water (used in processes)	L	Env-8	–	0.2	0.3	0.5	n/a	0.2	0.4	0.667	1	0.0587	0.0235	0.0392	0.0587
	Water (used in products)	L	Env-9	–	0.1	0.12	0.14	n/a	0.1	0.714	0.833	1	0.0441	0.0315	0.0367	0.0441
Chemical used	Cleaning and washing chemicals (sodium hypochlorite, detergents, etc.)	Kg	Env-10	–	0.4	0.5	0.6	n/a	0.4	0.667	0.8	1	0.0522	0.0348	0.0418	0.0522
	Preservatives and conditioners (benzoates, emulsifiers, anti-foaming agents, etc.)	Kg	Env-11	–	3	3.5	4	n/a	3	0.75	0.857	1	0.0571	0.0428	0.0489	0.0571
Air emissions	Carbon dioxide (CO_2)	Kg	Env-12	–	6.23	6.63	7	n/a	6.23	0.89	0.940	1	0.0522	0.0465	0.0491	0.0522
	Carbon monoxide (CO)	Kg	Env-13	–	0.0059	0.0063	0.0066	n/a	0.0059	0.894	0.937	1	0.0473	0.0423	0.0443	0.0473
	Sulfur oxides (SO_X)	Kg	Env-14	–	0.0059	0.0063	0.0066	n/a	0.0059	0.894	0.937	1	0.0441	0.0394	0.0413	0.0441
Wastewater	Chemical oxygen demand (COD)	mg/L	Env-15	–	15500	16500	17353	n/a	1550	0.893	0.939	1	0.0506	0.0452	0.0475	0.0506
	Biological oxygen demand (BOD)	mg/L	Env-16	–	1700	1850	2033	n/a	1700	0.836	0.919	1	0.0489	0.0409	0.0450	0.0489
	Suspended solid	mg/L	Env-17	–	4500	4800	5030	n/a	4500	0.895	0.9375	1	0.0489	0.0438	0.0459	0.0489
Solid waste	Biodegradable waste (food remains, cardboards, etc.)	g	Env-18	–	3	4	6	n/a	3	0.5	0.75	1	0.0555	0.0277	0.0416	0.0555
	Non-biodegradable waste (plastic, tin, etc.)	g	Env-19	–	4.5	5	6.5	n/a	4.5	0.692	0.9	1	0.0604	0.0418	0.0543	0.0604

Table 7. Economic inventory data.

Aspect Category	Indicators	Measuring Units	Indicators' ID	±	Indicators' Scores			C_n^+	C_n^-	Normalized Scores			Indicators' Weights	Normalized Weighted Scores		
					Min.	Most Likely	Max.			Min.	Most Likely	Max.		Min.	Most Likely	Max.
Cost	Raw materials	MYR	Eco-1	–	10	11	11.5	n/a	10	0.870	0.909	1	0.0808	0.0702	0.0734	0.0808
	Packaging materials	MYR	Eco-2	–	0.21	0.23	0.26	n/a	0.21	0.808	0.913	1	0.0786	0.0635	0.0718	0.0786
	Fixed assets (buildings, machines, equipment, etc.) depreciation	MYR	Eco-3	–	2.2	2.3	2.5	n/a	2.2	0.88	0.957	1	0.0590	0.0520	0.0565	0.0590
	Labor	MYR	Eco-4	–	2	2.2	2.3	n/a	2	0.8696	0.9091	1	0.0744	0.0647	0.0676	0.0744
	Maintenance	MYR	Eco-5	–	0.4	0.5	0.6	n/a	0.4	0.6667	0.8	1	0.0701	0.0468	0.0561	0.0701
	Environmental fines (for pollutants, etc.)	MYR	Eco-6	–	0	0	0	n/a	0	0	0	0	0.0680	0	0	0
	Utility (water, electricity, etc.)	MYR	Eco-7	–	0.71	0.8	0.83	n/a	0.71	0.8554	0.8875	1	0.0808	0.0691	0.0717	0.0808
	Defective products	MYR	Eco-8	–	0.08	0.09	0.1	n/a	0.08	0.8	0.8889	1	0.0680	0.0544	0.0605	0.0680
	Research and development	MYR	Eco-9	–	0.11	0.13	0.14	n/a	0.11	0.7857	0.8462	1	0.0765	0.0601	0.0647	0.0765
	Training	MYR	Eco-10	–	0.005	0.006	0.007	n/a	0.005	0.7143	0.8334	1	0.0611	0.0436	0.0509	0.0611
	Advertisement and promotion	MYR	Eco-11	–	0.14	0.2	0.27	n/a	0.14	0.5185	0.7	1	0.0638	0.0331	0.0446	0.0638
Profit	Revenue	MYR	Eco-12	+	20.5	21	21.5	21.5	n/a	0.9535	0.9767	1	0.0765	0.0730	0.0747	0.0765
	Profit	MYR	Eco-13	+	5	5.5	6	6	n/a	0.8333	0.9167	1	0.0765	0.0638	0.0701	0.0765
	Subsidy or tax relief from government	MYR	Eco-14	+	0.11	0.13	0.14	0.14	n/a	0.7857	0.9286	1	0.0659	0.0518	0.0612	0.0659

MYR = Malaysian Ringgit.

Table 8. Social inventory data for quantitative indicators.

Aspect Category	Indicators	Measuring Units	Indicators' ID	±	Indicators' Scores			C_n^+	C_n^-	Normalized Scores			Indicators' Weights	Normalized Weighted Scores		
					Min.	Most Likely	Max.			Min.	Most Likely	Max.		Min.	Most Likely	Max.
Labor wellbeing	Training and development	Number of workers given trainings	Soc-S-1	+	4	5	5	5	n/a	0.8	1	1	0.0465	0.0372	0.0465	0.0465
	Occupational health and safety (OHS)	Number of workers involved in OHS related incidents	Soc-S-2	–	1	2	3	n/a	1	0.333	0.5	1	0.0440	0.0146	0.0220	0.0440
	Health insurance	Number of workers having insurance provided by the company	Soc-S-3	+	4	5	5	5	n/a	0.8	1	1	0.0364	0.0292	0.0364	0.0364
	Reward and appreciation	Number of workers given reward and appreciation	Soc-S-4	+	4	5	5	5	n/a	0.8	1	1	0.0431	0.0345	0.0431	0.0431
Labor satisfaction	Turnover	Number of workers	Soc-S-5	–	1	1	2	n/a	1	0.5	1	1	0.0461	0.0230	0.0461	0.0461
	Absenteeism	Number of working days	Soc-S-6	–	1	1	2	n/a	1	0.5	1	1	0.0427	0.0214	0.0427	0.0427
Customer satisfaction	Customer complaints	Number of complaints	Soc-S-7	–	1	2	3	n/a	1	0.333	0.5	1	0.0352	0.0117	0.0176	0.0352
	Regular customers	Number of customers	Soc-S-8	+	13	15	22	22	n/a	0.591	0.682	1	0.0377	0.0223	0.0257	0.0377
Community and society wellbeing	Efforts against corruption	Number of programs organized	Soc-S-9	+	0	1	1	1	n/a	0	1	1	0.0377	0	0.0377	0.0377
	Efforts to reduce health, safety and environmental hazards	Number of programs organized	Soc-S-10	+	0	1	1	1	n/a	0	1	1	0.0477	0	0.0477	0.0477
	Efforts to promote religious and ethnic harmony	Number of programs organized	Soc-S-11	+	0	1	1	1	n/a	0	1	1	0.0390	0	0.0390	0.0390
	Local employment	Number of workers	Soc-S-12	+	4	5	5	5	n/a	0.8	1	1	0.0427	0.0342	0.0427	0.0427
	Engagement with community (knowledge transfer programs, product development programs, etc.)	Number of programs organized	Soc-S-13	+	1	1	3	3	n/a	0.333	0.333	1	0.0465	0.0155	0.0155	0.0465
Community and society satisfaction	Community complaints	Number of complaints	Soc-S-14	–	1	1	2	n/a	1	0.5	1	1	0.0364	0.0182	0.0364	0.0364
	Community compliments	Number of compliments	Soc-S-15	+	2	3	5	5	n/a	0.4	0.6	1	0.0330	0.0132	0.0198	0.0330

Table 9. Social inventory data for qualitative indicators.

Aspect Category	Indicators	Measuring Units	Indicators' ID	±	Indicators' Scores			C_n^+	C_n^-	Normalized Scores			Indicators' Weights	Normalized Weighted Scores			Single Value
					Min.	Most Likely	Max.			Min.	Most Likely	Max.		Min.	Most Likely	Max.	
Labor rights	Fair salary	VL to VH	Soc-F-1	+	3	4	4	4	n/a	0.75	1	1	0.0452	0.0339	0.0452	0.0452	0.0433
	Equal opportunity or non-discrimination	VL to VH	Soc-F-2	+	3	4	4	4	n/a	0.75	1	1	0.0440	0.0330	0.0440	0.0440	0.0421
	Freedom of association	VL to VH	Soc-F-3	+	3	4	4	4	n/a	0.75	1	1	0.0377	0.0283	0.0377	0.0377	0.0361
Working conditions	Decent working hours (compliance with regulations)	VL to VH	Soc-F-4	+	2	3	4	4	n/a	0.5	0.75	1	0.0465	0.0232	0.0349	0.0465	0.0349
	Decent workload (compliance with regulations)	VL to VH	Soc-F-5	+	2	4	4	4	n/a	0.5	1	1	0.0440	0.0220	0.0440	0.0440	0.0403
Customer wellbeing	Halal food	VL to VH	Soc-F-6	+	3	5	5	5	n/a	0.6	1	1	0.0424	0.0254	0.0424	0.0424	0.0396
	Safe food	VL to VH	Soc-F-7	+	3	5	5	5	n/a	0.6	1	1	0.0440	0.0264	0.0440	0.0440	0.0410
	Fat/sugar/salt free or organic food options	VL to VH	Soc-F-8	+	2	3	3	3	n/a	0.667	1	1	0.0364	0.0243	0.0364	0.0364	0.0344
	Labeling (sources, calories, nutrients, ingredients, instructions, etc.)	VL to VH	Soc-F-9	+	3	4	4	4	n/a	0.75	1	1	0.0452	0.0339	0.0452	0.0452	0.0433

VL to VH = Very Low to Very High; n/a = not applicable.

4.3. Assessment of Qualitative Indicators based Sub-System

As described in detail in Section 3, the qualitative indicators were evaluated through the fuzzy logic approach. The fuzzy membership grades and linguistic terms as presented in Tables 1 and 2 were used for the input and output variables. A fuzzy rule base was constructed at each aspect category level (labor rights, working conditions, and customer wellbeing) and three FISs were created. The fuzzy logic toolbox of Matlab software was used as a simulator. Figure 2 presents a final configuration example of the Mamdani-type FISs.

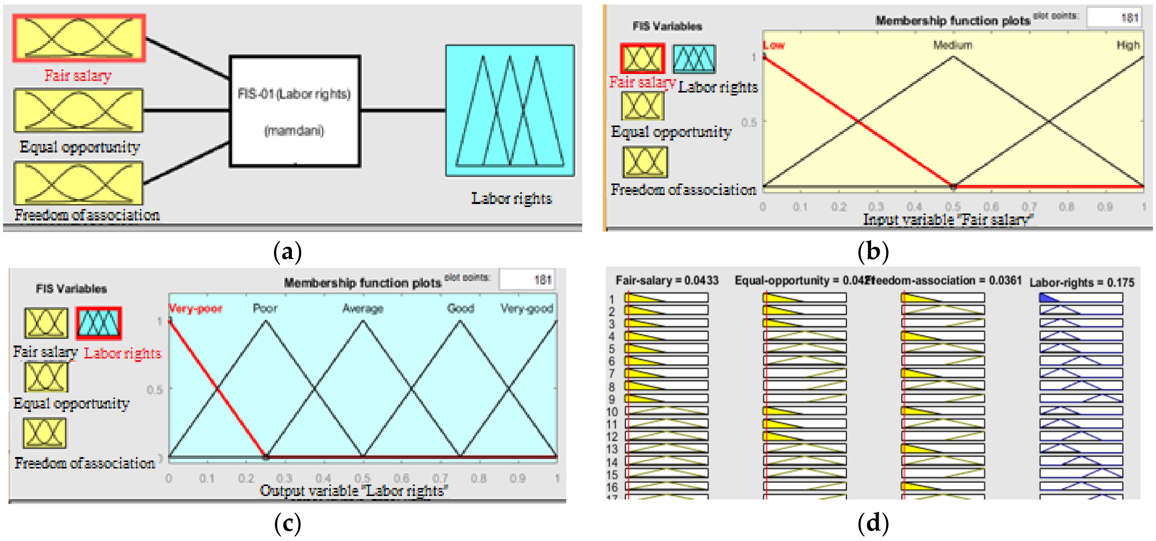


Figure 2. Fuzzy modeling and assessment (**a**) Fuzzy Interference System (FIS) model in Matlab; (**b**) Membership functions of input variable; (**c**) Membership functions of output variable; (**d**) Rule-based evaluation.

The grades of membership functions were used to create the rules. Some examples of rules from the rule bases are presented in Table 10.

Table 10. Examples of rules for the fuzzy models.

Rules
If (Fair salary is low) and (Equal opportunity or non-discrimination is low) and (Freedom of association is low) then (Labor rights are very poor)
If (Fair salary is low) and (Equal opportunity or non-discrimination is low) and (Freedom of association is medium) then (Labor rights are poor)
If (Fair salary is low) and (Equal opportunity or non-discrimination is medium) and (Freedom of association is high) then (Labor rights are average)
If (Decent working hours are low) and (Decent workload is high) then (Working conditions are average)
If (Decent working hours are medium) and (Decent workload is high) then (Working conditions are good)
If (Decent working hours are high) and (Decent workload is high) then (Working conditions are very good)
If (Halal food is low) and (Safe food is low) and (Fat/sugar/salt free or organic food options are medium) and (Labeling is medium) then (Customer wellbeing is poor)
If (Halal food is low) and (Safe food is low) and (Fat/sugar/salt free or organic food options are high) and (Labeling is high) then (Customer wellbeing is average)
If (Halal food is low) and (Safe food is high) and (Fat/sugar/salt free or organic food options are high) and (Labeling is medium) then (Customer wellbeing is good)

Performance of Qualitative Indicators Based Sub-System

After running the FISs, the defuzzified scores were obtained at each aspect category level. Table 11 presents the performance score based on qualitative indicators for each aspect category.

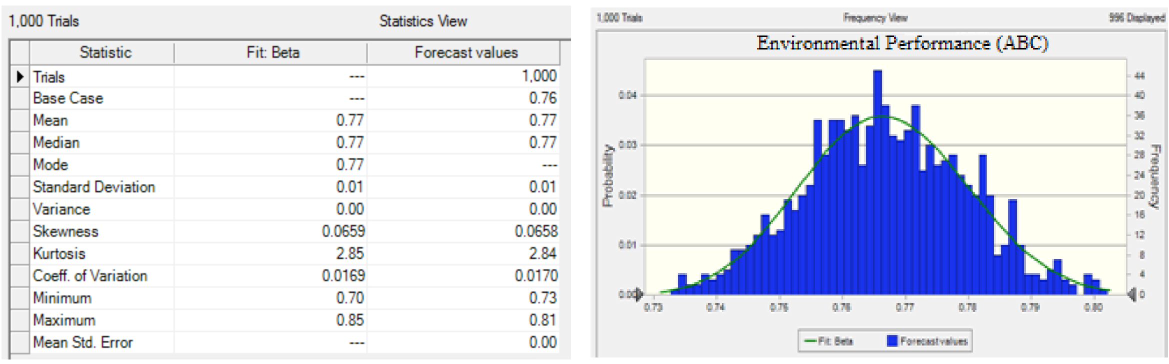
Table 11. Aspect category performance based on FISs.

Number	Aspect Category	Score
1	Labor rights	0.175
2	Working conditions	0.171
3	Customer wellbeing	0.172

The overall performance of the qualitative indicators based sub-system was calculated by adding up the scores of all three aspect categories. These values were directly summed up because all the aspect categories were having the same direction of impact on sustainability. The performance score of the qualitative indicators based sub-system was 0.518.

4.4. Assessment of Quantitative Indicators Based Sub-System

As mentioned earlier, the quantitative indicators were first processed through Monte Carlo simulation and then fuzzy logic. Using triangular distributions and three-point normalized and weighted data, the Monte Carlo simulation was performed 1000 times at each indicator level. The average simulated scores of indicators were added up to get the dimension level performance. For example, there were 19 environmental indicators, thus, the simulation was performed for all 19 indicators and then the average simulated scores of indicators were summed up to obtain the environmental performance. The same procedure was followed for the other two dimensions. Figure 3 shows the stochastic simulation outputs in pictorial forms.


1,000 Trials — Statistics View

Statistic	Fit: Beta	Forecast values
Trials	---	1,000
Base Case	---	0.76
Mean	0.77	0.77
Median	0.77	0.77
Mode	0.77	---
Standard Deviation	0.01	0.01
Variance	0.00	0.00
Skewness	0.0659	0.0658
Kurtosis	2.85	2.84
Coeff. of Variation	0.0169	0.0170
Minimum	0.70	0.73
Maximum	0.85	0.81
Mean Std. Error	---	0.00

(**a**) (**b**)

Figure 3. Simulation outputs (based on indicator level) (**a**) Simulated environmental performance; (**b**) Distribution fitting of performance outputs.

Performance of Quantitative Indicators Based Sub-System

The performance of each sustainability dimension, i.e., environmental, economic and social was generated based on the average simulated scores of quantitative indicators in the respective dimension. The scores for all three dimensions are presented in Table 12.

Table 12. Dimension level performance based on Monte Carlo simulation.

Number	Sustainability dimension	Score
1	Environmental	0.77
2	Economic	0.43
3	Social	0.16

The dimension level performance scores of quantitative indicators were used to construct another FIS in order to get a score for the quantitative indicators based sub-system. As mentioned earlier, FIS was employed to solve the problem of different directions of impact of sustainability dimensions. The overall performance score of the quantitative indicators based sub-system generated by the FIS was 0.404.

4.5. Total TBL Based Sustainability Index

The total TBL based sustainability index was calculated by adding up the weighted scores of the two sub-systems: qualitative indicators based sub-system and quantitative indicators based sub-system. The total sustainability index shows the weighted contribution of each sub-system. The weights of the quantitative indicators based sub-system (0.837) and qualitative indicators based sub-system (0.163) were calculated based on the indicators' weights in each sub-system, as given in [78]. Table 13 shows the total sustainability index of the case company.

Table 13. Total TBL based sustainability index.

<table>
<tr><th>Sub-System Name.</th><th>Modeling Approach</th><th>Model Name</th><th>Model Score</th><th>Sub-System Level Score</th><th>Weight</th><th>Total TBL Sustainability Index</th></tr>
<tr><td rowspan="3">Qualitative indicators based sub-system</td><td rowspan="3">Fuzzy logic (three models)</td><td>Labor rights</td><td>0.175</td><td rowspan="3">0.518</td><td rowspan="3">0.163</td><td rowspan="6">0.42</td></tr>
<tr><td>Working conditions</td><td>0.171</td></tr>
<tr><td>Customer wellbeing</td><td>0.172</td></tr>
<tr><td rowspan="3">Quantitative indicators based sub-system</td><td rowspan="3">Monte Carlo simulation (three models)</td><td>Environmental</td><td>0.77</td><td rowspan="3">0.404</td><td rowspan="3">0.837</td></tr>
<tr><td>Economic</td><td>0.43</td></tr>
<tr><td>Social</td><td>0.16</td></tr>
</table>

As already mentioned, the sustainability performance was indexed between 0 and 1. Five ranges were defined in order to categorize the sustainability performance as given in Table 4. For example, if the index is between the range of 0.0–0.19, then the performance is considered very poor. The total sustainability index of the case company was 0.42 which fell into the "Average" sustainability performance range.

5. Discussion and Analysis

This section presents a useful analysis and discussion of the results. These results were discussed with respect to the outputs of the fuzzy and stochastic models, total sustainability index and contribution to uncertainty.

For the qualitative indicators, as depicted in Figure 4, the aspect category of labor rights was comparatively performing better with a score of 0.175. It was followed by customer wellbeing (0.172) and working conditions (0.171). Based on the direction of impact, higher scores of these aspect categories mean better performance. Comparatively, the better score of the labor rights aspect category could be attributed mainly to the better performance of the case company with respect to fair salary, equal opportunity and freedom of association. In comparison, the working conditions aspect category showed lower performance which was based on decent working hours and decent workload. Grounded on these findings, the case company might increase its sustainability performance by putting more efforts and resources to improve the situations of decent working hours and decent workload. Overall, no aspect category scored 0.2 or higher and this showed that various opportunities exist for improvement. In the same way, the results of the stochastic models could also be analyzed.

For dimension level analysis, both scores pertaining to the social dimension (quantitative indicators with 0.16 and qualitative indicators with 0.518) were added, just for comparison purposes. At the dimension level, as discussed earlier, a lower score of the environmental and economic dimensions, and a higher score of the social dimension represent better performance. From the results, comparatively, the social dimension with a score of 0.678 (by adding 0.16 and 0.518) was performing better. Between the economic and environmental dimensions, the former showed relatively better performance (0.43) than the latter (0.77). The poorer score of the environmental dimension might be attributed to the considerable amount of air emissions and polluted wastewater coming out from the case company. With respect to the economic dimension, the profit based indicators have better scores than the cost related indicators.

Figure 4. Aspect category performance based on qualitative indicators.

The total TBL sustainability index (0.42) marked the case company's performance as average. Nevertheless, the company's performance was still far from the ideal sustainability level. In other words, there were various challenges to cope with and different opportunities to improve its sustainability performance. For example, the performance could be improved by focusing more on the low performing sustainability areas.

In addition, reducing uncertainties in the input variables is desirable for effective sustainability assessment. Theoretically, less uncertainties lead to more reliable probabilistic estimates. However, generally reducing uncertainty in any input variable will not necessarily result in the same magnitude of refinement in the output [81]. An analysis was presented to show how much each sustainability dimension contributed to the uncertainty or variability of the output using the Crystal Ball software.

The results of the analysis (Figure 5) showed that the social dimension contributed more to the output variance for the case company. It was followed by the environmental and economic dimensions of sustainability. In this way, the overall variability can be better and effectively reduced by focusing more efforts on the social dimension of sustainability.

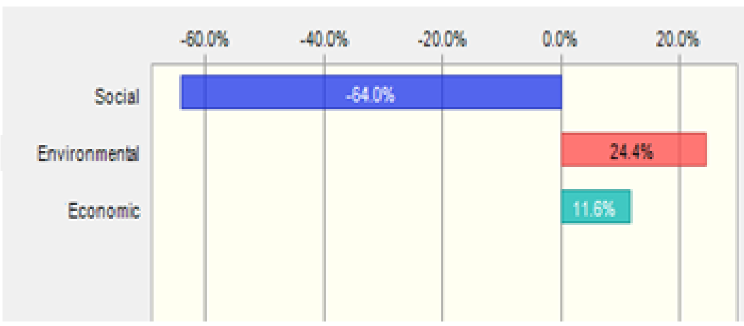
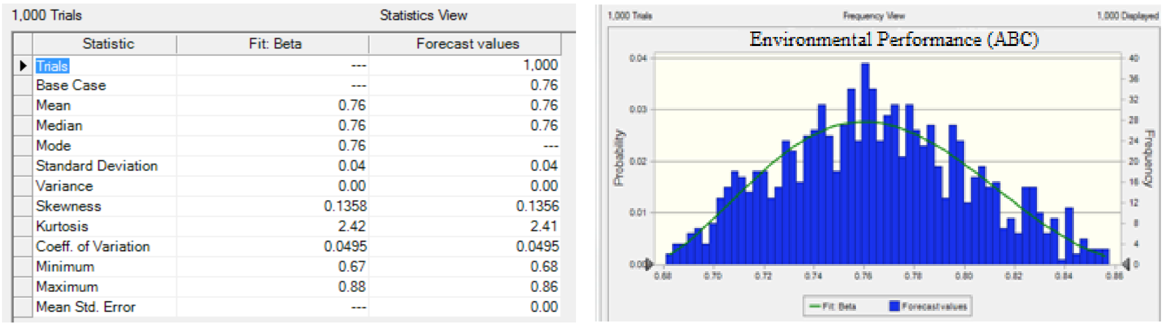


Figure 5. Contribution of each dimension to uncertainty.

6. Validation

Validation was performed to check the robustness of the developed method. In order to achieve this, instead of performing Monte Carlo simulation at each indicator level, it was done directly at each dimension level. In this regard, a cumulative distribution was calculated for each dimension before conducting the simulation. The cumulative distribution of each dimension was aggregated from the individual triangular distributions of the indicators in the respective dimension. The simulation was run 1000 times for each of the dimensions and the validation results were compared with the previous results. Figure 6 presents the dimension level simulation outputs.



1,000 Trials Statistics View

Statistic	Fit: Beta	Forecast values
Trials	---	1,000
Base Case	---	0.76
Mean	0.76	0.76
Median	0.76	0.76
Mode	0.76	---
Standard Deviation	0.04	0.04
Variance	0.00	0.00
Skewness	0.1358	0.1356
Kurtosis	2.42	2.41
Coeff. of Variation	0.0495	0.0495
Minimum	0.67	0.68
Maximum	0.88	0.86
Mean Std. Error	---	0.00

(**a**) (**b**)

Figure 6. Simulation outputs (based on dimension level): (**a**) simulated environmental performance; (**b**) distribution fitting of performance outputs.

Validation Results and Discussion

The new scores calculated for each dimension after conducting the simulation in a different way (simulation at the dimension level) are presented in Table 14. The analysis showed that there was only a difference of 0.01 in the environmental and economic performances, when the results in Tables 12 and 14 were compared. However, there was no difference in the performance of the social dimension. Overall, there was a difference of 0.01 in the total TBL sustainability index. These findings showed an insignificant difference and confirmed the robustness and reliability of the proposed method for sustainability assessment.

Table 14. Dimension level performance based on the validation approach.

Number	Sustainability dimension	Score
1	Environmental	0.76
2	Economic	0.42
3	Social	0.16

7. Implications

This novel research has various important implications. Firstly, it discussed the development and demonstration of a comprehensive and integrated sustainability assessment method. This new method integrates stochastic and fuzzy approaches in order to deal with uncertainties in a comprehensive way. This integration, which was overlooked in previous methods, has made sustainability assessment more precise and realistic. The proposed method is equally useful for practitioners as well as researchers. Practically, the method has been demonstrated and tested via a case study in the Malaysian food manufacturing industry. Practitioners could employ this method to evaluate and track their company's sustainability level and performance over time. Researchers could also use it to assess and compare the sustainability performance of food manufacturing activities.

In addition, keeping in view the constraints of resources, some companies are involved in the assessment of only one dimension of sustainability (for example, environmental). This method could also be used individually if separate assessment of one dimension is required. However, at a later stage, such companies might apply all the dimensions in order to have a comprehensive performance evaluation.

Last but not least, this study has shown the important utilization of Monte Carlo simulation and fuzzy logic for sustainability assessment purposes. It could guide researchers on how these two approaches are utilized and integrated to produce useful and reliable assessment results.

8. Conclusions

Current sustainability assessment studies face various challenges. The problems are related to the usage of an applicable, weighted and comprehensive set of sustainability indicators, analysis and quantification of stochastic and fuzzy uncertainties simultaneously, inclusion of the TBL concept of sustainability, assessment of sustainability in developing countries where limited databases and resources are available, etc. There is a need for the development of a new sustainability assessment method that can overcome the deficiencies of previous approaches. Thus, the main objective of this article was to develop and test a comprehensive and integrated stochastic-fuzzy sustainability assessment method. In this regard, Monte Carlo simulation and fuzzy logic were used in an integrated way to address the stochastic and fuzzy uncertainties. The proposed method combined the benefits of Monte Carlo simulation with the advantages of fuzzy inference.

Based on the weighted and comprehensive nature of its indicators, this method helps to provide more reliable and precise results. A real-world case study dealing with sustainability assessment of a Malaysian food manufacturing company was conducted to test the applicability and functionality of the proposed method. The case company showed an average sustainability performance with a total TBL based sustainability index of 0.42. The results revealed that, along with other measures, the sustainability performance of the case company might be improved more effectively by decreasing the amount of air emissions, polluted wastewater, etc., and improving the working conditions. In essence, the results showed that the developed method is useful for evaluating sustainability performance in terms of a total sustainability index within a system containing complicated uncertainties.

Apart from its advantages, this research had its own limitations. Firstly, only one case study was reported in this research. More studies in the future will confirm the usability of the developed method. Secondly, the case study was based on a gate-to-gate system boundary for assessment purposes. Future work could assess the sustainability level of food manufacturing activities by covering the supply chain stages or increasing the assessment boundary.

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