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Sustainable Supplier Selection Using Integrated Data Envelopment Analysis and Differential Evolution Model

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P A P E R I N F O	A B S T R A C T
Chronicle: *Received: 27 September 2019* *Revised: 09 February 2020* *Accepted: 04 March 2020* **Keywords**: *Supplier Selection.* *Sustainability.* *Sustainable Supply Chain.* *Sustainable Supplier Selection.* *Differential Evolution.* *DEA.* *Pharmacy.*	Nowadays, increasing environmental and social awareness has led numerous industries to adopt Sustainable Supply Chain Management (SSCM). Sustainable Supplier Selection (SSS) is considered as a very important and primary step of achieving an SSCM. SSS is a Multi-Criteria Decision Making (MCDM) problem and is very intricate for its nature. This study aims to evaluate and rank sustainable suppliers using Data Envelopment Analysis (DEA) which is a popular model for measuring the productive efficiency of decision-making units effectively and is also able to handle MCDM problems. To avoid some inherent limitations of DEA, an evolutionary algorithm Differential Evolution (DE) is used to solve the DEA model. This integrated DEA-DE model provides more accurate efficiencies and is verified through a case study in a pharmaceutical company. Employing this easy and fast model to assess sustainable suppliers will help industries and suppliers to move forward towards achieving and maintaining sustainability and thus will increase the overall performance of SSCM.

1. Introduction

All operations relevant to the circulation and transformation of products and services, along with their corresponding data flows, from material sources to end customers and management which control and integrate all such steps and processes, internally and externally are covered by the supply chain. This system acts as a connection between the inputs of an organization and its outputs. Traditionally faced challenges including reducing costs and transportation times, ensuring just-in-time delivery, etc. along with the rising environmental costs of these networks and the increasing demand from customers for environmentally friendly products have motivated many companies to consider sustainability as a new dimension of effective and profitable supply chain management. Sustainable Supply Chain Management (SSCM) is the management of goods, products, data and capital flows, as well as cooperation among firms on the supply chain, whereas taking under consideration, shareholder and customer requirements-based goals from all three dimensions (social, environmental, and economic) of sustainable development. All members within the chain from suppliers to top management need to be affined with sustainability to obtain a sustainable supply chain. The selection of green and

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sustainability-focused suppliers in industrial supply chains could be critical to raise strategic advantage, business performance, and revenue stream.

Supplier selection has been one of the most important functional activities in the supply chain throughout the decades. The researchers studied supplier evaluation, selection, and development and highlighted its significance in business performance and business process improvement [1, 2]. In the search for the best approach to select suppliers, several processes and methods like Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), and fuzzy based approaches, etc. have been widely used [3].

Managers in this changing manufacturing culture, are now hoped to work on conventional criteria such as improved quality, lower costs, reduced lead times, and increased flexibility while considering ecological issues at the same time. This has led to a new direction of research: Sustainable Supplier Selection (SSS). SSS includes many criteria comprising of lead-time, price delivery performance, speed, quality, CO2 emission, reliability, greenhouse effect, reusability, and carbon foot printing, etc. Konys [4] presents a methodological and practical background for capturing and handling knowledge about green supplier selection criteria.

Supplier selection is a Multi-Criteria Decision Making (MCDM) issue [5] containing both quantitative and qualitative criteria. Data Envelopment Analysis (DEA) which is a well-known nonparametric model for efficiency evaluation of multiple Decision-Making Units (or DMUs) is used in this study. It is utilized to quantify the efficiency of multiple suppliers considering multiple input and output criteria. Differential Evolution (DE) is an improved genetic algorithm-based technique, used for optimization problems. It optimizes a problem to improve a candidate solution in respect of a specified quality measure. In this study, an integrated model of DEA, a non-parametric method and metaheuristics like DE is used for selecting a sustainable supplier. Later on, a case study has been done using this model in a pharmaceutical company of Bangladesh named ‘‘Novartis’’. Criteria were selected based on previous researches and company demand. Sustainable suppliers were evaluated and ranked using both DEA and integrated DEA-DE model. This study compares both results and selects the supplier with the highest efficiency from the second list where suppliers’ efficiencies show clear differences.

2. Literature Review

In the course of the most recent couple of years, numerous scientists have dealt with the supplier selection problems to create appropriate strategies. With respect to the systematic strategies utilized in the process of supplier selection, broad research of selection strategies in the field of supplier selection has been carried out by De Boer et al. [6] and Ha and Krishnan [7]. Ho et al. [8] checked on the writing of the MCDM and analytical approaches for supplier assessment and determination. Broad single model methodologies have been suggested for choosing supplier, for example, the Analytical Hierarchy Process (AHP) [9, 10], Analytic Network Process (ANP) [11], Rough Weighted Aggregated Sum Product Assessment (WASPAS) method [12], MACBETH [13], Weighted Utility Additive (WUTA) [14], DEA [15], Genetic Algorithm (GA) [16], etc. In a supplier selection process, it is very often to integrate various procedures and models to improve the primary goal or nature of the models. Ha and Krishnan [7] proposed a hybrid approach by combining AHP with DEA and Neural Network (NN) which further uses cluster analysis to select a supplier. Fuzzy logic is a vastly used mechanism to solve many real-world problems where decision takers preferences are involved. Hence, in the field of supplier selection, many hybrid models under a fuzzy environment like fuzzy-AHP [17], integrated fuzzy TOPSIS and MCGP [18], fuzzy-ANP [19], etc. are also used by researchers. In numerous sourcing, many scientists have tried mathematical programming, for example, multi-objective mixed-integer linear programming [20], Goal Programming (GP) [21], Z-Numbers [22], etc.

Presently, ecological components are a major subject which offers ascend to the new worldview of concentrating on green supply chains. Other than the hypothetical accentuation on, a great deal of work has been done generally where the specialists have recommended distinctive models and devices and innovations for sustainable supplier selection. The authors processed a hybrid MCDM model using a Fuzzy AHP (FAHP) and Green DEA (GDEA) model to identify the weight of all criteria of a supplier’s selection process in [23] and then applied GDEA to rank all potential supplier lists. Yu and Hou [24] approached a more effective MMAHP model (combined MCDM-multiplicative AHP model) than the traditional AHP model in automobile industries to facilitate green supplier selection which can also avoid potential rank changing when new suppliers are added. Cover some other commonly used methods for sustainable supplier selection [25, 26]. A hybrid model of Total Interpretive Structural Modeling (TISM) and Fuzzy Analytic Network Process (FANP) is proposed to assess socially responsible supplier [27]. Quan et al. [28] proposed a weighted grey incidence decision approach for green supplier evaluation and selection in a process industry.

There is a good amount of research work in the field of supplier and sustainable supplier selection. Most of these research works are traditional approaches where weights are assigned based on a set of question-answer of experts. As a result, those works are biased by decision takers preferences and unable to provide accurate results. Though many of them used several methods to handle this subjectivity, those are not very optimal. When DEA works with a production function, does not need to estimate functional parameters. Therefore, DEA is free of subjectivity and thus provides more accurate efficiencies and ideal for MCDM [29]. For a long time, DEA is a very popular approach among researchers for evaluating efficiencies of DMUs. Lists some of the applications of DEA [30, 31]. In some cases, data may be imprecise, vague and inconsistent. Edalatpanah [32] proposed a new DEA model with neutrosophic input and output to deal with such situations. Tavassoli [35] proposed a stochastic-fuzzy DEA model to evaluate and rank sustainable suppliers in the presence of all deterministic, stochastic and fuzzy data in a unified framework. Differential Evolution (DE) is a population-based evolutionary algorithm that can optimize regardless of the nature of the objective function [34]. Mogha [35] introduced Differential Evolution (DE) to solve DEA based models. Many programming based integrated models have already been developed and used in various research. For example, goal Programming-Based Data Envelopment Analysis framework (GP-DEA) [36] and hybrid Genetic/Immune Strategy based green DEA (GIS-DEA) [37] have been approached to evaluate and select a sustainable supplier. Khoshfetrat and Hosseinzadeh [38] introduced a Nonlinear Programming (NLP) model to derive the true weights for pairwise comparison matrices in AHP and then the proposed model was solved using a GA approach.

In this study, we aim to select a sustainable supplier based on social, economic and environmental criteria using an integrated DEA–DE model. DEA solves the fractional objective function by converting it to a linear model (CCR or BCC) which increases the chance of errors. To minimize this error and to get optimum efficiencies, a DEA based DE model is approached because of its capability of handling nonlinear functions.

3. Methodology

As of now specified, DEA is the foundation method for this research and further DE is incorporated with DEA for selecting the sustainable supplier. The following six concurrent stages comprise all the essential steps:

- Problem selection: The primary step is to identify the problem to be evaluated for execution, and determining the sustainable supplier is the objective of this study.
- Criteria selection: The selection of input-output criteria mainly depends upon the type of the problem. As per the problem demand, those are carefully chosen.
- Data collection: All relevant data are collected from the organization where the research will be executed.
- Efficiency assessment using DEA: Once all the data are collected along with the selection of the problem, it's time to formulate the mathematical model and solve them. In the current study, the authors use DEA to assess supplier performance.
- Apply further improvement: To minimize the limitations of DEA, an evolutionary-based algorithm is approached to solve DEA. In this case, we have coordinated DEA with DE to evaluate supplier performance more accurately and make a ranking of sustainable suppliers.
- Final efficiency assessment: This is the last step in determining and assessing suppliers' performance or effectiveness.

In the accompanying segments, we quickly depict DEA and DE. During this study, all the stages of the stated methodology were followed consecutively. While selecting input and output criteria, the economic, social and environmental demands for sustainability were considered carefully. Some data may be imprecise. The scale of collecting data was set keeping in mind its consequence. After achieving the efficiency, the suppliers were ranked.

3.1. Data Envelopment Analysis (DEA)

DEA is a non-parametric technique model to evaluate the efficiency of DMUs, which was proposed by Charnes et al. (CCR model) [39] and developed by Banker et al. (BCC model) [40]. Above mentioned models differ from each other based on their differing assumptions about the return to scale. BCC model uses the variable return to scale while the constant return to scale is used in the CCR model. This linear programming based technique measures the efficiency of input and output based DMUs. The aim is to improve the relative efficiency of the DMUs by defining an appropriate set of weights.

$$\text{Efficiency} = \frac{\mathit{Weighted}\ \text{sum of o/p}}{\text{Weighted sum of i/p}}. \tag{1}$$

To calculate the decision-making efficiency, we can describe as follows:

$$\text{Max } \mathrm{E_m} = \frac{\sum_{\mathrm{k=1}}^{\mathrm{o}} \mathrm{w_k}\ \mathrm{Output_{k,m}}}{\sum_{\mathrm{l=1}}^{\mathrm{I}} \mathrm{z_l}\ \mathrm{Input_{l,m}}}. \tag{2}$$

$$0 \le \frac{\sum_{\mathrm{k=1}}^{\mathrm{o}} \mathrm{w_k Output_{k,n}}}{\sum_{\mathrm{l=1}}^{\mathrm{I}} \mathrm{z_l Input_{l,n}}} \le 1, \qquad \mathrm{n} = 1,2, \dots \mathrm{N}. \tag{3}$$

$$\mathrm{w_k}, \mathrm{z_l} \ge 0;\ \forall\ \mathrm{k}, \mathrm{l}. \tag{4}$$

Here, $E_m = m^{th}$ DMU's efficiency, l=1 to I, k=1 to O and n=1 to N.

$Output_{k,m} = k^{th}$ Output of m^{th} DMU.

w_k= weight of output $Output_{k,m}$.

$Input_{l,m} = l^{th}$ input of m^{th} DMU.

z_l= weight of $Input_{l,m}$.

$Output_{k,n}$ is the k^{th} output and $Input_{l,n}$ is the l^{th} input of the n^{th} DMU and n=1,2…,m...N.

This fractional model is solved using linear programming technique after transforming it into a linear program. Every DMU's effectiveness is comparatively maximized when there are N numbers of DMUs. *Eqs. (5-8)* represent the linear program version of the fractional model presented in the *Eqs. (2-4)*. CCR's general DEA model can be presented as:

$$\mathrm{Max} = \mathrm{E_m} \sum_{k=1}^{o} \mathrm{w_k Output_{k,m}}. \tag{5}$$

$$\mathrm{s.t.} \quad \sum_{l=1}^{I} \mathrm{z_l Input_{l,m}} = 1. \tag{6}$$

$$\sum_{k=1}^{o} \mathrm{w_k Output_{k,n}} - \sum_{l=1}^{I} \mathrm{z_l Input_{l,n}} \leq 0, \ \forall \ \mathrm{n}. \tag{7}$$

$$\mathrm{w_{k,} z_l} \geq 0; \ \forall \ \mathrm{k, l}. \tag{8}$$

BCC model's general form can be presented as:

$$\mathrm{Max} = \mathrm{E_m} \sum_{k=1}^{o} \mathrm{w_k \ Output_{k,m}} + \mathrm{z_{ol}}. \tag{9}$$

$$\mathrm{s.t.} \quad \sum_{l=1}^{I} \mathrm{z_l Input_{l,m}} = 1. \tag{10}$$

$$\sum_{k=1}^{o} \mathrm{w_k Output_{k,n}} - \sum_{l=1}^{I} \mathrm{z_l Input_{l,n}} + \mathrm{z_{ol}} \leq 0, \ \forall \ \mathrm{n}. \tag{11}$$

$$\mathrm{w_k, z_l} \geq 0; \ \forall \ \mathrm{k, l}. \tag{12}$$

z_{ol} is not restricted in the sign. When the efficiency score of any DMU is 1 the DMU is considered efficient otherwise it is less efficient.

3.2. DE Model

DE is a population-based searching method that uses NP variables as the population of D dimension of solution space for each generation. When we have no idea about solution space, DE starts with the randomly generated asset of solution. This set of solutions is called the population. Let $P = \{X_i^G, i = 1,2, \dots NP\}$ be the population at any generation G, where $X_i^G = \left\{x_{1,i}{}^G, x_{2,i}{}^G, \dots x_{D,i}{}^G\right\}$ is D-dimensional solution vector and NP is the population size. Simple DE (DE/rand/1/bin) operations such as mutation, crossover and selection are defined as follows:

Mutation. In DE, mutation functions as the main search engine. It extends the space of the search. Three random vector $X_{r_1}^G, X_{r_2}^G, and\ X_{r_3}^G$ are arbitrarily selected for a given target vector X_i^G, where $i \neq r_1 \neq r_2 \neq r_3$. The weighted difference of two of the vectors is added to the third. So, the mutant vector $V_i^G = \{v_{1,i}{}^G, v_{2,i}{}^G, \dots v_{D,i}{}^G\}$ is defined as:

$$V_i^G = X_{r_1}^G + F * (X_{r_2}^G - X_{r_3}^G). \quad (13)$$

It is known as (DE/rand/1) mutation strategy. The value of the scaling factor (F) falls within (0, 2). This scaling factor (F) regulates the differential variation $(X_{r_2}^G - X_{r_3}^G)$ amplification.

Crossover. Crossover is aimed at increasing the variety of mutants. It incorporates promising results from the previous generation.

Let, X_i^G is target vector, $V_i^G = \{v_{1,i}{}^G, v_{2,i}{}^G, \dots\ v_{D,i}{}^G\}$ is a mutant vector, so s new vector (trial vector), $U_i^G = \{u_{1,i}{}^G, u_{2,i}{}^G, \dots u_{D,i}{}^G\}$ is generated as:

$$u_{j,i}^G = \begin{cases} v_{j,i}^G, & \text{if } C_r < \text{rand}(0,1) \quad \forall\, j = j_{rand} \\ x_{j,i}^G & \text{otherwise} \end{cases}. \quad (14)$$

Here, rand (0, 1) is a uniform random number between 0 and 1; C_r is the crossover constant, j_{rand} is any figure: 1,2,3,…,D.

Selection. The main concept in selection is, “The fittest will survive”. Among the trial and target vector U_i^G and X_i^G, the fittest one is passed for the next generation.

Choose the most suitable vector for the next generation population from the trial and target vector.

$$X_i^{G+1} = \begin{cases} U_i^G, & \text{if } f(U_i^G) \leq f(X_i^G) \\ X_i^G & \text{otherwise} \end{cases}. \quad (15)$$

These three operations continue till a certain terminating threshold is not met.

4. Case Study

Novartis Bangladesh Limited provides solutions for healthcare. The company is a multinational group of companies that specializes in researching, developing, producing and marketing a range of pharmaceutical-led healthcare products. They focus on science-based healthcare sectors that are rapidly growing, reward innovation, and enhance the lives of patients. In our study, we conduct our research for Novartis (Bangladesh) Limited. Most of the cases, they outsourced raw materials. So, while purchasing from outside the company, they maintain some code for the suppliers to keep the sustainability alive. Novartis (Bangladesh) Limited requires its suppliers to comply with the standards defined in the supplier code. This study used related API (Active Pharmaceutical Ingredient) purchasing data of Novartis. They needed twenty different types of API in different quantity and there was a total of fifteen local and international suppliers in the choice list.

4.1. Criteria Setting

Here, in this study, the criteria are being taken from Novartis (Bangladesh) Limited. These criteria cover all three economic, social, and environmental aspects of sustainability and are grouped into the following input and output set.

- Input Criteria
  - Price ($): Price is the amount of money that has to be paid to acquire a given product.
  - Lead Time (LT) (in days): It is the time taken by suppliers between which they collect, produce and ship the order to satisfy customer requirements.
  - Supplier Reputation (SR) (10 scales): It is the standard of reputation that is perceived through the eyes of customers based on the supplier previous performance.
- Output Criteria
  - Service Quality (SQ) (100 scales): An evaluation of how well a delivered service conforms to the expectations of the client. Business operators often assess the quality of service provided to their customers to enhance their service, identify issues rapidly, and better evaluate customer satisfaction.
  - CO2 Emission (in grams): Carbon emissions are carbon releases into the atmosphere. Talking about carbon emissions is just talking about greenhouse gas emissions; the key reason for climate change.
  - Quality (100 scales): Quality has a pragmatic interpretation as something's non-inferiority or superiority; it's also defined as purpose fitness.

4.2. Data Collection and Data Analysis

Table 1. *Collected raw data of suppliers.*

Suppliers	**Criteria INPUT**			**OUTPUT**		
	Price ($)	**Lead Time (days)**	**Supplier Reputation (10 scales)**	**Service Quality (100 scales)**	**CO_2 Emission**	**Product Quality (100 scales)**
1	*11895*	*6*	*2*	*57*	*38*	*55*
2	*12350*	*4*	*5*	*35*	*40*	*62*
3	*11650*	*5*	*1*	*43*	*49*	*66*
4	*9950*	*3*	*3*	*77*	*38*	*87*
5	*12500*	*5*	*5*	*53*	*51*	*81*
6	*11500*	*13*	*7*	*59*	*36*	*88*
7	*13450*	*8*	*6*	*76*	*27*	*69*
8	*13250*	*15*	*8*	*89*	*39*	*57*
9	*10500*	*14*	*7*	*68*	*31*	*71*
10	*11750*	*16*	*9*	*73*	*8*	*95*
11	*12050*	*17*	*8*	*58*	*9*	*79*
12	*13600*	*9*	*5*	*74*	*17*	*82*
13	*10640*	*10*	*7*	*83*	*15*	*67*
14	*11400*	*14*	*4*	*71*	*13*	*92*
15	*12750*	*16*	*6*	*90*	*19*	*78*

4.3. Associated Software and Parameter

After collecting and analyzing necessary data, in the first phase, the DEA was implemented using DEAP solver software version 2.1. The case study was an output-oriented Variable Returns to Scale (VRS) model. Differential evolution is an evolutionary algorithm. We use Python language for writing the program and PyCharm software to run the program. The fitness value taken in 30 runs is considered as the average fitness value, and upon reaching max-iteration, the program is terminated. We set the boundary limit for input and output criteria. The Pop Size (NP) was taken 100, scale factor (F) was taken between 0-2 while cross over rate (Cr) was between 0-1 and max iteration was kept as 3000.

5. Results and Discussion

Here in the first phase while applying the model of DEA, three efficient suppliers are found and those are 3rd, 4th, and 13th number suppliers. In the second phase, the integrated DEA-DE model has been applied. Every execution of the program provides different numeric efficiency of each supplier where the efficiency score for each supplier is very close but not the same in every run. To get an accessible and usable efficiency score, an average efficiency was calculated by running the code 20 times. The average calculation makes the suppliers' efficiencies more precise and acceptable. It evaluates the 4th supplier as most efficient and thus ranked 1 among the fifteen suppliers.

Table 2. *Efficiency and final ranking of suppliers.*

Supplier	DEA		DE	
	Efficiency	**Rank**	**Efficiency**	**Rank**
1	*0.963*	*4*	*0.953021*	*3*
2	*0.927*	*5*	*0.861121*	*6*
3	*1*	*1*	*0.896026*	*4*
4	*1*	*1*	*0.978978*	*1*
5	*0.995*	*2*	*0.966195*	*2*
6	*0.875*	*10*	*0.888389*	*5*
7	*0.785*	*12*	*0.855847*	*7*
8	*0.867*	*11*	*0.803284*	*8*
9	*0.975*	*3*	*0.751647*	*10*
10	*0.925*	*6*	*0.754826*	*9*
11	*0.893*	*9*	*0.705842*	*12*
12	*0.747*	*13*	*0.701379*	*13*
13	*1*	*1*	*0.697312*	*14*
14	*0.923*	*7*	*0.747032*	*11*
15	*0.909*	*8*	*0.685868*	*15*

Supplier efficiency compared with the two technique depict that in some case, supplier with higher efficiency in DEA like 13th supplier get lower efficiency in DE. On the other hand, suppliers with lower efficiency in DEA like 6th and 7th get higher efficiency in the second phase. We assume it as an error due to the absence of proper constraints handling technique while performing DE. The result also shows that the integrated DEA-DE model provides an optimized sustainable supplier by reducing three efficient suppliers to one efficient supplier. The comparable histogram is shown in *Fig. 1*.

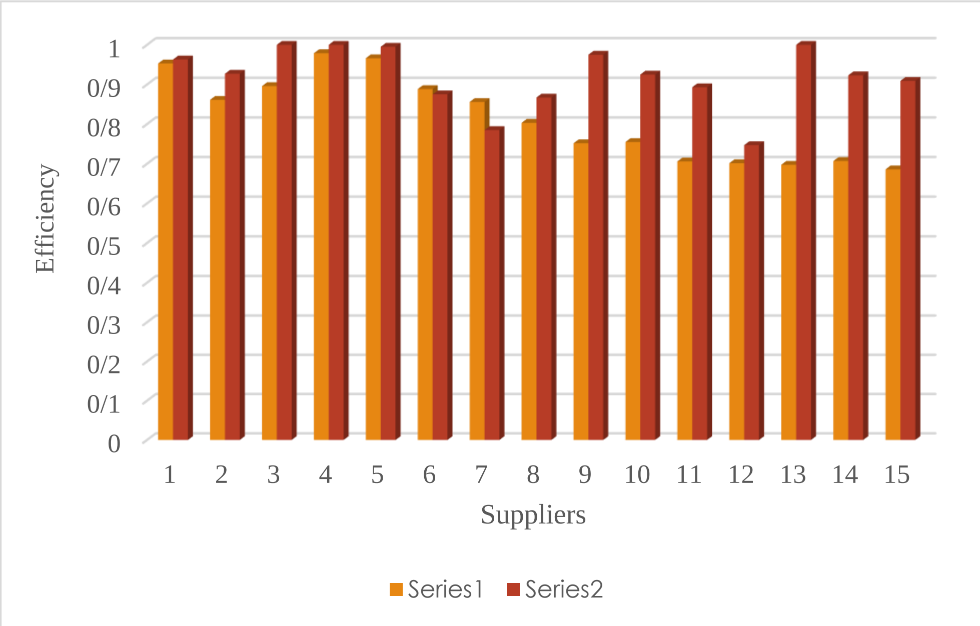

Fig. 1. *Histogram of supplier efficiency by both DE and DEA model (Series 1: DE & Series 2: DEA).*

6. Conclusion

To make good the responsibilities to our mother nature and also to compensate for increasing carbons in the atmosphere, sustainable and green activities like selecting green suppliers are now getting more importance from business organizations besides raising competitive advantage. Therefore, attempting to develop and improve decision models that more accurately perform the supplier selection and evaluation procedure seems essential. This study used the DEA method at the beginning to evaluate the sustainable supplier efficiency on a comparison basis in the presence of the imprecise data. At the very beginning, the most important and sensitive element of DEA, which is criteria, have been selected. These criteria must fulfill sustainability conditions. After identifying the input and output criteria, in the first stage, all suppliers were assessed utilizing DEA model by DEAP software. DEA is a well-known method for evaluating multiple homogenous unit's efficiencies. Although, it is a popular performance measuring technique, DEA comes along with certain intrinsic disadvantages and as an attempt towards minimizing these disadvantages, DE has been incorporated. To propose an effective method to select sustainable supplier, DE and DEA are integrated using the same objective function in the second phase. A program is written in python language and with the help of this program, the efficiency is measured for every supplier thus rank them. A case study of a pharmaceutical company shows that when DEA is integrated with DE, discretionary power increases. By integrating DEA and DE, this new framework provides more reliable and acceptable results than a single DEA model. Companies and industries can use this integrated model for moving along the path of economic, social, and environmental aspects at the same time to boost up their supply chain by adopting a truly sustainable supplier. In this study, the problem that we have worked on is in its initial stage of exploration. This model can be improvised further by integrating with other developed models that serve the same purpose.

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