A stochastic approach for evaluating production planning efficiency under uncertainty

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Article Info

Article history:

Received Nov 10, 2022
Revised Mar 25, 2023
Accepted Apr 7, 2023

Keywords:

Efficiency
Manufacturing
Production planning
Robust stochastic data envelopment analysis
Small and medium sized enterprise

ABSTRACT

Planning production is an essential component of the decision-making process, which has a direct bearing on the effectiveness of production systems. This study's objective is to investigate the efficiency performance of decision-making units (DMU) in relation to production planning issues. However, the production system in a manufacturing environment is frequently subject to uncertain situations, such as demand and labor, and this can have an effect not only on production but also on profit. The robust stochastic data envelopment analysis model was proposed in this study with maximizing the number of outputs as the objective function thus means of handling uncertainty in input and output in production planning problems. This model, which is based on stochastic data envelopment analysis and a method of robust optimization, was proposed with the intention of providing an efficient plan of production for each DMU of stage production. The model is applied to small and medium-sized businesses (SMEs), with inputs consisting of the cost of labor, the number of customers, and the quantity of raw materials, and the output consisting of profit and revenue. It has been demonstrated through implementation that the proposed model is both efficient and effective.

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1. INTRODUCTION

The process of planning production involves making decisions that will help locate resources needed for production in an efficient manner. In other words, production planning involves allocating required products to resources in many production systems. At this time, the manufacturing environment is dealing with an unrelenting increase in demand amid uncertainty. Consequently, there is a need to maximize both productivity and product quality. In a market where there is intense competition, the primary goal of production planning is to determine the optimal level of production, optimal levels of inventory, and so on [1], [2]. In the realm of production planning, not only is it necessary to guarantee production effectiveness even in the face of unpredictability [3]–[5], but it is also essential to guarantee customer satisfaction and long-term growth [6]. In a real-world scenario, Pastor *et al.* [7] put the production plan into action at the woodturning company.

Production planning is an essential issue in production systems that aims at effective planning for a company's future production. Our paper is contribution is to evaluate the efficiency of the production system and the coordination of all production activities in order to optimize the company is objectives. This efficient production system will be used in the company's next production plan to maximize profits. Data envelopment analysis (DEA) is one method for evaluating performance. DEA is a performance evaluation method. The DEA method [8] uses linear programming to compare the efficiency of a group of similar decision-making units (DMUs). Organizational productivity-DEA-depends on measurement and comparison of the effectiveness of organizational units for instance, hospitals surgical units [9], [10], education [11], [12], business companies [13], [14], banks [15]–[17], and so on are becoming increasingly important.

In traditional DEA assumes all data values are known. However, real-world inputs and outputs are imprecise and ambiguous. Kao and Liu [18] proposed a model for determining the membership functions of fuzzy efficiency scores when some or all inputs are fuzzy numbers. Stochastic programming addresses, as implemented in [19]–[21] created a stochastic p-robust to adversely affect the objective function, and Shakouri *et al.* [22] proposed a robust system for estimating efficiency in input uncertainty. Furthermore, research by Ben-Tal *et al.* [23], [24] on robust optimization in benchmark problems revealed that a limited data variation could make an uncertain solution infeasible.

The previous study measured efficiency using a robust DEA model [25] and a stochastic DEA method [26]. This paper developed a robust stochastic DEA model for output-oriented production system efficiency measurement in small business enterprises (SMEs). The proposed model maximizes outputs with uncertain inputs and outputs. The result of efficient production is assumed to be the planned production for the following season.

The remainder of this work is organized as follows. The following section provides an overview of the related studies and methodology, describing DEA and stochastic DEA. Section 3 provides a summary of our research on the proposed model of robust DEA and a numerical example of small business enterprise cases. Finally, in section 4, we present our findings by summarizing the paper's contribution.

2. METHOD

2.1. Framework data envelopment analysis model

DEA compares the efficiency of similar DMUs using linear programming. The DEA identified the most efficient unit, also called the "best practice" unit, and employs that unit to assess the effectiveness of each DMU. It computes the amount of resources saved by making every unit efficient. Thus, DMU efficiency cannot be determined. DEA compares DMU output-to-input ratios to determine relative efficiency, and the efficiency frontier is the convex combination of the most efficient units [27]. The classic output-oriented DEA model as (1):

$$\text{Maximize } \sum_{r=1}^{n} u_r y_{r0}$$

$$\text{s.t } \sum_{i}^{m} v_i x_{i0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0; j = 1,2,\dots,n$$

$$v_i \geq 0; i = 1,2,\dots,m$$

$$u_r \geq 0; r = 1,2,\dots,s \tag{1}$$

2.2. Stochastic data envelopment analysis model

Stochastic programming is one of methods to dealing uncertainty in DEA. Khodabakhshi [28] developed additive input relaxation model by replacing stochastic version in chance constrained programming. El-Demerdash *et al.* [29] proposed changing the stochastic DEA model from output-oriented to input-oriented with chance-constrained output. Tavana *et al.* [30] developed the stochastic data and ideal point concept-based common set of weights (CSW) model to rank DMUs. Stochastic programming addresses uncertainty. According to (1) assumed there are n DMUs, with m inputs and s outputs denoted by $\bar{u}_r = \bar{u}_{1r}, \bar{u}_{2r}, \dots, \bar{u}_{sr}$, where each $\bar{u}_{rj}(r = 1,2,\dots,s)$ have a probability distribution. In this paper, the stochastic data envelopment model adopted from [31] with every inputs transformed into outputs with $\alpha_j=\alpha$ is parameter that represent a risk level, and also $\beta_j=\beta$ is parameter that is aspiration level. By maximizing the expected efficiency, the stochastic DEA model is defined as (2):

$$\text{Maximize } y^t \bar{u}_0$$

$$\text{s.t } \beta_j - y^t \bar{u}_j \geq y^t b_j \varphi^{-1}(1-\alpha_j),\ j = 1,2,\ldots,N \quad (2)$$

where φ denotes cumulative distribution function of the normal distribution and φ^{-1} indicated that inverse function. $b_j = (b_{rr})_{sx1}$ denotes $s-$ dimension vector and $\bar{u}_0$ denotes the mean output value in the objective function.

2.3. Propose robust stochastic DEA model

The robust optimization (RO) model is popular for data uncertainty. This approach seeks near-optimal and likely feasible solutions. Bertsimas and Thiele [32] using RO to handling uncertainty data with inventory problems, strategic project growth planning [33]. With following [34] the framework model of RO as (3):

$$\text{Minimize } c'x$$

$$\text{s.t } Ax \geq b$$

$$x \in X \quad (3)$$

Stochastic programming addresses uncertainty, in this study the robust optimization model was integrated with stochastic DEA model to handling the uncertainty multi-inputs and multi-outputs data. This model's parameters and decision variables are explained as:

- Sets
  - J = The set of DMU
  - I = The set of input
  - R = The set of output
- Decision variables
  - DMU_j = The quantity of DMU j
  - $\tilde{\tilde{x}}_{i0}$ = The quantity of random input i at DMU0
  - $\tilde{\tilde{y}}_{i0}$ = The quantity of random output r at DMU0
  - $\tilde{\tilde{y}}^t_{r0}$ = The quantity of random transform output r at DMU0
- Parameters
  - α_j = The unit level of risk of DMU j
  - β_j = The unit level of aspiration of DMU j
  - $\tilde{u}_r$ = The unit random output r
  - $\tilde{v}_i$ = The unit random input i

The formulation to robust stochastic DEA models as (4)-(8):

$$\text{Maximize } \sum_{r=1}^{s} \tilde{u}_r \tilde{\tilde{y}}_{r0} \quad (4)$$

$$\text{Subject to: } \sum_{r=1}^{j} \tilde{\tilde{y}}^t_{r0}\left(b_j \varphi^{-1}(1-\alpha_j) + \tilde{u}_r\right) \leq \beta_j \ \forall\, j \in J \quad (5)$$

$$\sum_{r=1}^{m} \tilde{v}_i \tilde{\tilde{x}}_{ij} \geq \beta_j \quad (6)$$

$$\sum_{i=1}^{r} \tilde{v}_i \tilde{\tilde{x}}_{i0} = 1 \quad (7)$$

$$\sum_{r=1}^{s} \tilde{u}_r \tilde{\tilde{y}}_{rj} - \sum_{i=1}^{m} \tilde{v}_i \tilde{\tilde{x}}_{ij} \leq 0 \quad (8)$$

2.4. The algorithm of robust stochastic DEA model

As the previous section to final formulation of the mathematical robust stochastic DEA, we can also formulate the algorithm be as:

```
Step 1: input: i, j, r
Step 2: set: i=1
While i≤n
•  Input: random input, random output
•  ũr > 0, ṽi > 0
•  i=i+1
   End while
```

```
Step 3: set i=1
       While i≤r
1. Formulate robust stochastic DEA (θj)
2. Calculate the θj
3. If θj=0 is false
                  Print "DMUi:θj * 100%, Efficient"
               Else
                  Print "DMUi:θj * 100%, Inefficient"
               Endif
4. i=i+1
       Endwhile
Step 4: set i = 1
       For i in range (Len(DMU)-1):
               Idx_min=i
               For j in range (i + 1, len DMU)):
               If DMU [j] < DMU[idx_min]:
               Idx_min=j
               Temp=DMU [idx_min]
               DMU[idx_min]=DMU[i]
               DMU[i]=temp
               Endfor
       Endfor
Endfor
```

3. RESULT AND DISCUSSION

In this study, a robust stochastic data envelopment analysis model developed, which applies for small and medium-sized enterprises (SMEs), one of which is a bakery company that produces six types of cookie products filled with peanuts. These cookies are used as a one of souvenir in the city. By following the steps of the algorithm that were formulated in the previous section, we get the following:

3.1. Step 1

Their production system in this paper using only one manufacture and six product families including cookies with mung beans (CMB), cookies with black beans (CBB), cookies with red beans (CRB), cookies with mung bean cheese (CMBC), cookies with black bean cheese (CBBC), and cookies with red bean cheese (CRBC). In Table 1, inputs include labor cost, raw material cost, machine capacity, and demand. Every bakery company's product represents as DMUs. In this case of study, the efficiency of the production performance of each DMU will be measured with a robust stochastic DEA model. The best production on the current system is used to find the efficiency value of each DMU. The optimal efficiency production assumed that can be used to plan production for the next period.

Table 1. The data for production bakery's company in 2020

DMU_j	Type of products	Labor cost (I_1)	Raw material cost (I_2)	Machine capacity (I_3)	Number of demand (I_4)
1	CMB	74.880	365	2.954	29.217
2	CBB	53.260	275	3.676	25.802
3	CRB	43.205	360	7.784	15.500
4	CMBC	59.324	360	6.796	16.050
5	CBBC	61.245	357	8.675	17.170
6	CRBC	134.503	420	6.475	13.450

3.2. Step 2

In this paper, as the inputs data are the number of demands, labor cost, raw materials cost, machine capacity. Whereas the outputs are profit and revenue, as presented in the Table 2. Tables 1 and 2 indicate the uncertainty affected inputs and outputs. According to the report, the actual data from the manager bakery's company that the average of profits in 2020 was 14.499 million rupiah and the average of revenue also in 2020 was 28.784 million rupiah. In this paper, the robust stochastic DEA model is used to measure the efficiency of the production of SMEs in the bakery company that produces six types of products with the following production data in 2020.

3.3. Step 3

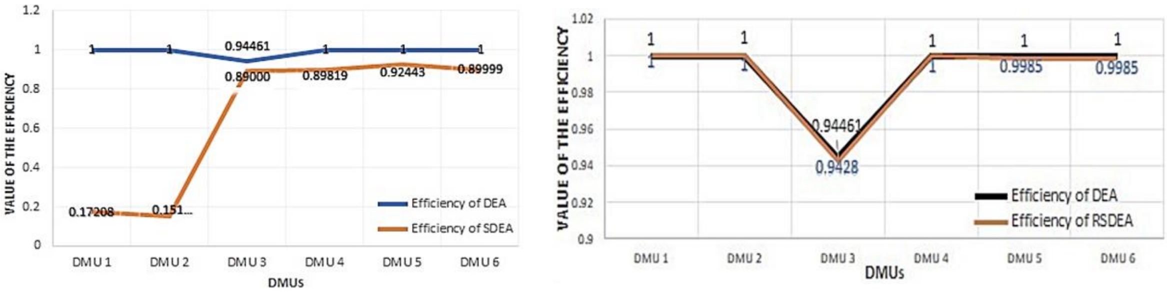
In this third step, each DMU is applied to the formulated model, and the efficiency value of each DMU is calculated and the percentage of each DMU is obtained. The performance effectiveness problem is solved through LINGO software version LINGO/WIN64 19.0.53. Table 3 describes value of the efficiency production from SMEs. By solving the model with each objective function of each DMU, a 100% efficiency value is produced, describing that production is optimal, and that means it can be used as a reference for production planning in the next period. The fourth step, which describes doing step 3 until all DMUs have been completed. Figure 1 shows the difference variation of efficiency values with DEA and SDEA in Figure 1(a) while variation efficiency values between DEA and RSDEA in Figure 1(b). Table 4 describes the result of the efficiency of DEA, SDEA and robust stochastic DEA.

Table 2. The data profits and revenue in 2020

DMU_j	Type of products	Profit (O_1)	Revenue (O_2)
1	CMB	12.370	25.650
2	CBB	12.450	25.715
3	CRB	15.500	35.820
4	CMBC	16.050	40.050
5	CBBC	17.170	39.280
6	CRBC	13.450	42.185

Table 3. The efficiency production of bakery company

DMU_j	Type of products	I_1	I_2	I_3	I_4	O_1	O_2	Efficiency
1	CMB	74.880	365	2.954	29.217	12.370	25.650	100%
2	CBB	53.260	275	3.676	25.802	12.450	25.715	100%
3	CRB	43.205	360	7.784	15.500	15.500	35.820	94%
4	CMBC	59.324	360	6.796	16.050	16.050	40.050	100%
5	CBBC	61.245	357	8.675	17.170	17.170	39.280	99%
6	CRBC	134.503	420	6.475	13.450	13.450	42.185	99%



(a) (b)

Figure 1. Differences variation efficiency values in (a) DEA and SDEA models and (b) DEA and robust stochastic DEA (RSDEA) models

Table 4. The result of the efficiency of DEA, SDEA and robust stochastic DEA (RSDEA) model

DMU_j	Type of products	DEA efficiency	SDEA efficiency	Robust stochastic DEA ($\alpha = 0.2$; $\beta = 0.90$)
1	CMB	1	1.720801	1
2	CBB	1	1.519667	1
3	CRB	0.9446112	0.8999742	0.9427615
4	CMBC	1	0.8981871	1
5	CBBC	1	0.9244337	0.9984741
6	CRBC	1	0.8999943	0.9984741

In this study, the robust stochastic DEA model is utilized to assess the efficiency of each DMU production in a bakery company, which is classified as a SMEs. As a DEA, it is utilized frequently in various models of performance evaluation. The study [35] utilized the DEA model to determine the optimal value of efficiency Turkey's SMEs. According to the findings presented in the paper, a comparison of the CCR and BCC models' efficiency values with scale efficiency was carried out. Wang *et al.* [36] utilized a stochastic DEA model to evaluate the effectiveness of production and waste gas treatment within the industrial sector in China. They use "=0.5" and "=0.05" in the SDEA model and in that paper to indicate that the performance on waste gas treatment is significantly worse or inefficient. As a result, Sadjadi *et al.* [37] utilized the robust counterpart of the super-efficiency DEA. They published using the stochastic DEA model, based on the chance constraint super-efficiency DEA model.

This article uses data production from SMEs that produce six different types of products in order to demonstrate the effectiveness of the proposed robust stochastic DEA model (4). This entire piece of research relies entirely on the findings of a bakery company in the year 2020 and their production of data. All of these products were analyzed in terms of their DMU equivalents to determine how efficient they were. In this particular scenario, the outputs should be maximized as much as possible. According to Table 3, which outlines the efficiency levels of each DMU, the production of DMUs 1 (CMB), 2 (CBB), and 4 (CMBC) is all 100%. Despite this, DMU 3, 5, and 6 have a poor efficiency rating. This is a consideration for the manager of the bakery company to improve their production at DMU, which has not been effective due to the nature of uncertainty in the amount of demand that affects the amount of profit and revenue. This method of effective production of DMU is utilized as a production plan in order to compete with other products of a similar nature that are currently available on the market.

On Table 4, describe how to obtain the DMU efficiency score by making use of each model DEA, stochastic DEA, and the robust stochastic DEA. When compared with using robust stochastic DEA and stochastic DEA model, the performance production achieved through the use of DEA model is more effective. These results are due to the fact that the assumption that the DEA model makes regarding the uncertainty of the inputs and outputs is not taken into consideration. However, the DEA stochastic model and the robust DEA stochastic model are applied in such a way that the level of reliability for each constraint is assumed to be 0.9. Because of this, we can deduce that "=0.2". That number indicates that the threshold for allowable perturbation at both the inputs and outputs has been set to 0.2. The results presented in Table 4 demonstrate that the efficiency of the SDEA is inferior to the efficiency of the robust stochastic DEA.

4. CONCLUSION

This study proposed and implemented the robust stochastic DEA model in order to evaluate the production efficiency of SMEs companies that produce six different types of products. This SMEs is a bakery that is growing in one of the provinces in Indonesia; their products are used as souvenirs, and the province in which it is developing is Indonesia. The performance of the proposed model suggests that the uncertainty level in the production efficiency score can be relied upon when taking into consideration the data. According to the findings, the manager of a small or SME can use the reliable method to estimate efficient.

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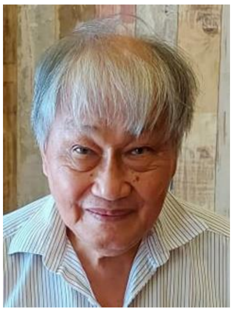

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