DEA Efficiency Assessment of Packaging Lines in A Pharmaceutical Industry

Abbas Al-Refaie, Ghaleb Abbasi, Ahmad Al-Hawadi

***Abstract*— This research evaluates the efficiency of two packaging lines: PK1 and PK2, over the year 2020 using window analysis and data envelopment analysis (DEA) techniques, including CCR, BCC, and slack-based model (SBM). Seven-decision making units (DMUs) of the window of six months were considered. For each DMU, the planned production quantity (PPQ), defect quantity (DQ), and idle time (IT) were set as the inputs, whereas the produced quantity was the output. Then, the technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) scores were calculated for all DMUs. Based on the PT and PTE scores, it is found that the efficiency scores of the PK2 line showed more stability properties during the year 2020 and were larger than their corresponding scores of PK1. Moreover, the SE scores indicated that pure technical inefficiency (PTIE) was the main contributor to technical inefficiency (TIE) for PK1 in all the seven DMUs, while the PTIE and SE were the contributors to TIE of PK2. The majority percentages of 61.90% and 52.38 % efficient lines for PK1 and PK2 were operating under constant returns to scale, respectively. Finally, the results of SBM revealed that the averages of input excess slacks of PK1 (PK2) in PPQ, DQ, and IT were 59.5793 (14.9193), 1.3275 (2.0703), and 58.2518 (12.8491), respectively. Moreover, the inefficiency scores by SBM were larger than their corresponding TIE values. In conclusion, the results of this research can guide decision-makers to the appropriate actions that reduce inefficiency scores and enhance lines' performance.**

***Index Terms*— BCC, CCR, inefficiency, slack-based models, window analysis**

I. Introduction

Today's harsh competition in the pharmaceutical market demands continual monitoring of operational and scale process efficiency. In the pharmaceutical sector, packaging processes are continually monitored to ensure the integrity and quality of products throughout the distribution chain. An efficient operation is regarded as one of the main objectives of a firm's management, which means that a firm achieves more outputs by consuming low input levels. Data envelopment analysis (DEA) is a nonparametric technique used to measure the relative efficiency of a group of homogeneous units; referred to as "decision-making units". (DMUs). Each DMU uses multiple inputs to produce multiple outputs [1-3]. Due to its solid theoretical basis, the traditional models of DEA have been widely adopted to assess efficiency in many real-world problems [4-6]. However, when a limited number of DMUs is available, those models are found ineffective. Alternatively, the DEA window analysis makes it feasible to observe how each DMU performs in different periods based on the principle of moving averages by treating each DMU in different periods as a separate unit [7-13]. DEA window analysis has been widely used in monitoring and assessing performance for a variety of business applications, including, banking [14-15], pharmaceutical [16-19], and energy efficiency and productivity [20].

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Al-Refaie is Professor of Industrial Engineering, University of Jordan, Amman, Jordan, (Corresponding author e-mail: abbas.alrefai@ju.edu.jo).

Abbasi is Professor of Industrial Engineering, University of Jordan, Amman, Jordan, (e-mail: abbasi@ju.edu.jo).

Al-Hawadi is an Industrial Engineering graduate (Master degree) of University of Jordan, Amman, Jordan, (e-mail: ahmad.s.alhawadi@gmail.com).

In this research, a pharmaceutical company aims at evaluating the efficiency of its packing lines; PK1 and PK2, and determining the sources of the inefficiency over a period from January to December 2020 using DEA window analysis. The results of this research shall provide valuable guidance to production engineers on how to assess the performance of its two packaging lines; PK1 and PK2, and develop operational and/or managerial means to operate efficiently. The remainder of this research including the introduction is outlined in the following sequence. Section II presents DEA models. Section III conducts data collection and analysis. Section IV presents the research results and discussion. Finally, conclusions are summarized in Section V.

II. DEA Models

DEA encompasses a variety of approaches to efficiency evaluation. These techniques are presented in the following subsections.

A. Technical and Pure-Technical Efficiency Models

Technical Efficiency (TE) is related to the productivity of inputs. Generally, the TE is a comparative measure of how well a process's inputs achieve its outputs, as compared to its maximum potential for doing so, as represented by its production possibility frontier [21]. A measure of TE under the assumption of constant returns-to-scale (CRS) is a measure of overall technical efficiency (OTE). Charnes-Cooper-Rhodes (CCR) model is one of the most well-known DEA models [1]. Consider a set of n DMUs. For DMU k, let y_{rk} (r = 1, ..., s) denote the level of r^{th} output and x_{ik} (i = 1, ..., m) be the level of the i^{th} input. The input-oriented CCR model is then used to measure the technical efficiency of a specific DMU k as follows [22-24]:

$$Min \quad \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{ik}, i = 1, ..., m \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk}, r = 1, ..., s \tag{3}$$

$$\lambda_j \geq 0, \tag{4}$$

θ unrestricted in sign

where the s_i^- and s_r^+ are the negative and positive slack variables, respectively. Here, $\varepsilon > 0$ is a so-called non-Archimedean element and is smaller than any positive real number. The optimal θ, θ^*, satisfies $0 \leq \theta^* \leq 1$. If θ^* equals one and all slacks are zeros, then the DMU under measurement is identified as TE-efficient. If θ^* equals one while at least one of the slacks is nonzero, this DMU is judged as weakly CCR-efficient. The CCR model states that a proportional increase in all inputs results in the same proportional increase in output. In other words, the CRS means that when an input increases by a factor α, the output increases by the same factor. In this case, the size of the operation of DMU is optimal. An input-oriented CCR model seeks to minimize inputs while satisfying at least the given output levels. Consequently, the objective value of CCR is designated TE, which reflects the firm's ability to obtain maximum output from a given set of inputs [25].

Further, the Banker, Charnes, and Cooper (BCC) model in DEA measures pure technical efficiency (PTE). The PTE ignores the impact of the scale size by only comparing a DMU to a unit of a similar scale [26-27]. The PTE assesses how a DMU utilizes its sources under exogenous environments; a low PTE implies that the DMU inefficiently manages its resources. It purely reflects the managerial performance to organize the inputs in the production process. Usually, the PTE is obtained by estimating the efficient frontier under the assumption of variable returns-to-scale (VRS). The DMU operates under variable returns to scale if it is suspected that an increase in inputs does not result in a proportional change in the outputs. To take VRS into account, the CCR model is extended to BCC models [22] as follows:

$$Min \quad \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \tag{5}$$

Subject to:

$$\sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{ik}, i = 1, ..., m \tag{6}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk}, r = 1, ..., s \tag{7}$$

$$\sum_{j=1}^{n} \lambda_j = 1, \tag{8}$$

$$\lambda_j \geq 0, \tag{9}$$

θ unrestricted in sign

A DMU that has an optimal θ (θ^*) equal to one and all slacks are zeros is then called BCC efficient. The DMU operates under variable returns to scale if it is suspected that an increase in inputs does not result in a proportional change in the outputs.

B. Scale Efficiency

The TE helps to determine inefficiency due to the input/output configuration as well as the size of operations. The TE is decomposed into two mutually exclusive and non-additive components: the PTE and scale efficiency (SE). This decomposition allows an insight into the source of inefficiencies. Thus, the PTE is used to capture managerial performance. The ratio of TE to PTE provides SE measure. The SE provides the ability of the management to choose the optimum size of resources, *i.e.*, to decide on the line's size or the scale of production that will attain the expected production level. The inappropriate scale size of a line (too large or too small) may sometimes be a cause of technical inefficiency. The scale inefficiency takes two forms: an increasing returns-to-scale (IRS) means that when an input increases by a factor α, the output increases by more than α. Whereas, a decreasing returns-to-scale (DRS) indicates that when an input increases by a factor α, the output increases by less than α [26]. In other words, DRS implies that an organization is too large to take full advantage of scale and has a supra-optimum scale size. In contrast, an organization experiencing IRS is too small for its scale of operations, and thereby it operates at a sub-optimum scale size. Finally, a process is treated as scale-efficient when it operates at CRS.

In practice to minimize costs and maximize revenues, a process has to operate at the most productive scale size *i.e.*, with CRS. The existence of IRS or DRS can be identified by the sum of intensity variables in the CCR model. If the sum of intensity variables is less (larger) than one, an IRS (DRS) results. The BCC model allows the decomposition of the TE into PTE and SE, where the relationship between them is expressed as:

$$SE = \frac{TE}{PTE} \tag{10}$$

In practice, SE measures how the scale size affects efficiency which helps management in choosing the optimal size of resources or production scale that will attain the expected level of production.

C. Window Analysis

When using the CCR and BCC models, an important rule of thumb is that the number of DMUs is at least twice the sum of the number of inputs and outputs. Otherwise, these models may produce numerous relatively efficient units. To resolve this difficulty, DEA window analysis [31] compares the performance of a DMU in any period with its performance in other periods as well as the performance of other DMUs. The window should be as small as possible to minimize the unfair comparison over time, but still large enough to have a sufficient sample size [32]. Assume that N DMUs (n = 1, ..., N) consume r inputs to produce s outputs and are observed in T (t = 1, ..., T) periods. Let DMU_n^t represent an n observation in period t with input vector X_n^t and output vector Y_n^t. If the window starts at time k ($1 \leq k \leq T$) with w ($1 \leq w \leq T-k$) width, then the matrices of inputs and outputs are respectively expressed as follows:

$$X_{kw} = \begin{bmatrix} x_1^k & x_2^k & \cdots & x_N^k \\ x_1^{k+1} & x_2^{k+1} & \cdots & x_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \cdots & x_N^{k+w} \end{bmatrix}, \tag{11}$$

$$Y_{kw} = \begin{bmatrix} y_1^k & y_2^k & \cdots & y_N^k \\ y_1^{k+1} & y_2^{k+1} & \cdots & y_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \cdots & y_N^{k+w} \end{bmatrix} \tag{12}$$

Substituting the inputs and outputs of DMU_n^t into the CCR or BCC model will produce the results of DEA window analysis.

D. SBM Model

The slack-based measure (SBM) makes its efficiency evaluation invariant to the units of inputs and outputs [33-35]. This property is known as "dimension-free" or "units' invariant." The SBM has the following important properties: (i) invariant concerning the unit of measurement of each input and output item, (ii) monotone decreasing in each input and output slack (Monotone). The optimal efficiency, ρ^*, using SBM is obtained by solving the following model [36]:

$$\rho^* = Min\ 1\text{-}\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}} \tag{13}$$

Subject to:

$$x_{ik} = \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^-, i=1,...,m \tag{14}$$

$$y_{rk} \le \sum_{j=1}^{n} \lambda_j y_{rj},\ \ r=1,...,s \tag{15}$$

$$\lambda_j \ge 0, j=1,...,n \tag{16}$$

$$s_i^- \ge 0, i=1,...,m \tag{17}$$

III. Data Collection and Analysis

The data were collected for two packing lines; PK1 and PK2, from the production reports over a period of one year (January to December 2020 DEA analysis, the planned production quantity (PPQ, unit), defect quantity (DQ, unit), and idle time (IT, unit) are considered inputs because these values are to be reduced. In contrast, the produced quantity in units (APQ) has to be increased, and hence it is set as the output for each DMU. The collected data for both packaging lines are listed in Table 1. Two DEA techniques will then be used to assess the DMU efficiency; the first technique adopts the traditional CCR and BCC models, while the second technique employs the SBM model.

A. Window Analysis Using CCR and BCC Models

The basic concept in window analysis is the consideration of each packaging line as a different one in each of the months listed at the top of Table 1 to obtain the scores listed in the rows that constitute the window. The stub on the left side indicates the window length and the periods covered.

a. Analysis of technical efficiency

The TE values were estimated using the CCR model for PK1 and PK2 and the results are then displayed in Table 2. For instance, the first row (1-6) in Table 2 extends from January to June 2020 for a window length of six months. The next row (2-7) starts in February and extends to July for another window, and so on. In data analysis, the rows are used to examine trends that occur in each window, whereas the columns are employed to examine stability properties. From Table 2, it is noted that:

(i) the TE averages listed in each column (month) show stable performance for both lines PK1 and PK2 because the differences between the efficiency values in each month are negligible. For example, in June (month 6) the TE values for PK1 are all equal to one for all six DMUs. This indicates a stable performance of both lines in each month of the year 2020, and hence the monthly average TE values are considered reliable for assessing the monthly performance.

(ii) some of the TE scores of each DMU are found equal to one. Nevertheless, the average TE scores are less than one for all seven DMUs for lines PK1 and PK2, and thereby DMUs are concluded as CCR-inefficient. The largest (smallest) average TE scores are 0.941 (0.889) and 0.969 (0.899) for lines PK1 and PK2, respectively.

(iii) the TE average scores for line PK2 are larger than their corresponding averages for line PK1 for all DMUs. The largest TE average (=0.941) for line PK1, which corresponds to DMU4, is less than the smallest TE average (0.9540) for line PK2. This indicates that the performance of line PK2 outperforms that of line PK1 during the year 2020.

(iv) the TE monthly averages for line PK2 are larger than their corresponding averages for line PK1 in almost all months. Further, the averages of TE averages for line PK1 and line PK2 are 0.899 and 0.969, respectively. To become CCR-efficient, the inputs of lines PK1 and PK2 shall be on average reduced by 10.13 % and 3.10 %, respectively.

(v) the monthly TE averages reveal that line PK1 is CCR-efficient (TE =1.0) in Months 5, 6, and 9. While, line PK2 is efficient in Months 4, 6, 7, and 11.

b- Analysis of pure technical efficiency

Contrary to TE which measures efficiency without scale consideration by comparing a DMU to other DMUs of the same size only, the PTE values were computed using the BCC model under the assumption of VRS. The PTE assesses managerial performance to organize inputs in the production process. Table 3 summarizes the estimated PTE values of all seven DMUs for the PK1 and PK2 1ines. The results show that:

(i) the monthly PTE averages reveal that line PK1 is found to only be BCC-efficient in five months (3, 5, 6, 9, and 11), whereas PK2 is found to only be BCC-efficient in eight months (4 to 9). The dispersion effect is not noticed in all months for both packaging lines.

(ii) all DMUs of line PK1 are identified as BCC-inefficient because the PTE averages are all less than one. The largest

PTE average (= 0.984) corresponds to DMU4, whereas the smallest PTE average (= 0.918) corresponds to DMU6. The average of PTE averages is 0.9312. Consequently, the elimination of inefficiency is achieved by an average input reduction of 6.88% is required for line PK1 to become BCC-efficient.

(iii) DMU6 is the only BCC-efficient DMU for line PK2. The largest PTE average (= 1.00) corresponds to DMU6, whereas the smallest average (= 0.968) corresponds to DMU1. The PTE average of averages of line PK2 (= 0.981) indicates that an average input reduction of 1.88% is needed for line PK2 to become BCC-efficient.

(iv) the PTE averages for line PK2 are larger than their corresponding PTE averages for line PK1. Consequently, the managerial performance of line PK2 surpasses that of PK1 during the year 2020 for all DMUs.

c- Analysis of scale efficiency

The SE was calculated by dividing TE by PTE. If TE and PTE are found equal, then SE equals one, and hence the scale operation size is optimal. Otherwise, returns-to-scale analysis is required to determine if the packaging line needs size expansion or reduction. When a line has a small size of the operation, or increasing IRS, then there shall a plan for expansion in the operation size. If most of the inefficiency is due to the large size of operations, or decreasing DRS, then a size reduction is suggested. Table 4 displays the estimated SE values, where it is noted that:

(1) the SE average of line PK1 is equal to one in four months; 5, 6, 9, and 12. While the SE averages of PK2 are equal to one in five months.

(2) the SE averages of PK1 are smaller than one for all DMUs; except DMU7. While the SE averages of line PK2 are only equal to one for DMU1 and DMU7.

(3) the SE averages of line PK2 are larger than their corresponding values of line PK1 for all DMUs. Moreover, the averages of SE averages for line PK2 are larger than their corresponding averages for line PK1.

The TE results show that PK2 operates in more periods at optimal size (CRS) than PK1. Moreover, more efforts are needed to adjust the size of the PK1.

d- Analysis of SBM

The SBM efficiency values were calculated as shown in Table 5 displays. The SBM scores reveal that:

(i) the optimal efficiency using SBM is smaller than its corresponding optimal CCR efficiency for both packaging machines because SBM accounts for all inefficiencies whereas CCR accounts only for "purely technical" inefficiencies. In other words, the SBM inefficiencies are larger than the TE inefficiencies.

(ii) PK1 is found SBM-efficient in two months (5 and 6), whereas PK2 is efficient in four months.

(iii) the average SBM efficiency is less than one for all DMUs in both packaging lines, and hence all DMUs of both packaging lines are SBM-inefficient during the year 2020. The largest average SBM-efficiency (= 0.766) for PK1 corresponds to DMU4, whereas the largest efficiency (= 0.865) for PK2 corresponds to DMU (7-12). Moreover, the SBM averages for line PK2 are larger than their corresponding averages for line PK1 at all DMUs. Consequently, line PK2 is concluded that is more SBM-efficient than line PK1.

IV. Results and discussion

A. Results and Discussion for Window Analysis Using CCR and BCC Models

Table 6 displays the calculated slacks in PPQ, DQ, IT, and APQ using the CCR and BCC models for both packaging lines. From Table 6, it is found that:

(i) the CCR model provides zero input excesses and output shortages in PPQ and APQ, respectively, for both lines PK1 and PK2. The IT input contributes the largest averages of excess slacks of 46.0802 and 13.554 for lines PK1 and PK2, respectively. Moreover, the input slack averages for DQ are 0.776 and 1.332.

(ii) for PK1, DMU7 and DMU4 have the smallest excess slacks of DQ (= 0.0) and IT (33.660), respectively. While for PK2, DMU5 and DMU7 have has the best utilization of DQ (= 0.014) and IT (= 6.2708), respectively. On other hand, the largest excess slacks of DQ (IT) are 1.008 (57.757) and 2.659 (21.695) corresponding to DMU3 and DMU2 for lines PK1 and PK2, respectively. Finally, the average differences of DQ (ΔDQ) and IT (ΔIT) between lines PK1 and PK2 are 0.556 and -32.527, respectively. Consequently, line PK2 utilizes inputs better than line PK1. Moreover, to achieve better performance, a reduction in IT input is required for both packaging lines.

Based on the obtained results, it is concluded that PK2 outperforms line PK1 in utilizing PPQ, DQ, and IT inputs to produce the same output (APQ). That is, line PK2 is concluded to be more technically efficient than line PK1 during the year 2020.

Table 6 also displays the estimated input slack values for PK1 and PK2, where the ΔDQ, ΔIT, and ΔAPQ between lines PK1 and PK2 are 0.074, -21.158, and -0.009, respectively. These values indicate that management efficiency in organizing the inputs of line PK2 outperforms that of line PK1.

The inefficiencies due to technical, pure technical, and scale efficiencies; TIE, PTIE, and SIE, respectively are summarized in Table 7. Generally, the TIE can be caused by either PTIE or SIE. From Table 7, it is found that:

(i) the TIE, PTIE, and SIE averages for line PK1 are larger than their corresponding values for line PK2 in all DMUs. The TIE average of averages (=0.0293), PTIE (=0.014), and SIE (=0.013) for line PK2 are smaller than their corresponding TIE (=0.085), PTIE (0.055), and SIE (=0.029) for line PK1. This implies that PK2 operated at a more efficient scale size than line PK1. Nevertheless,

managerial actions and scale size reduction/increase are required to improve the TE scores of both packaging lines.
(ii) PTIE is the main contributor to the TIE for all seven DMUs of line PK1 because the PTIE averages are larger than their corresponding SIE averages.
(iii) PTIE values of DMU1 to DMU3 and DMU7 cause the TIE for PK2, while SIE of DMU4 to DMU6 cause the TIE. Hence, TIE is concluded to be the main source of the PTIE, and thus management needs to enhance the utilization of the input resources.
(iv) the IRS, CRS, and DRS for PK1 (PK2) percentages are 2.38% (7.14%), 61.90% (52.38%), and 35.71% (40.48%), respectively. The total number of different lines (=7×6) is 42 for each packaging line. The results indicate that the highest percentages (= 61.90% and 52.38 %) of the different lines for PK1 and PK2 are operating at the most productive scale size and experiencing CRS, respectively. Whereas, the lowest percentages for PK1 and PK2 of 2.38% and 7.14%, respectively, are operating below their optimal scale sizes, and hence experiencing IRS. The policy implication of this finding is that decision-makers can enhance TE by increasing the scale size. The remaining 35.71% and 40.48% are operating in the zone of DRS, and thus downsizing seems to be an appropriate strategic option to reduce unit costs. In summary, the main contributor to TIE is the PTIE, while further improvement can be achieved in TE if the scale size is reduced.

Table 8 displays the causes of the TIE in both packaging lines. Comparing the monthly SIE and PTIE, it is noted that the PTIE is the major source of the monthly TIE because most of the monthly inefficiencies are incurred due to the PTIE for both packaging lines.

B. *Results Discussion for Window Analysis Using SBM Models*

Table 9 summarizes the calculated input excess slacks and output shortages for both packaging lines during the year 2020. It is noted that the averages of excess slacks in PPQ, DQ, and IT for line PK1 (PK2) are 59.579 (14.919), 1.328 (2.0703), and 58.252 (12.849), respectively. The largest excess slacks are observed in PPQ and IT for both lines and thus actions are needed to reduce the excesses of PPQ and IT. Nevertheless, line PK2 provides better performance than line PK1. Further, zero shortages in APQ appeared for both packaging lines. Finally, consistent conclusions regarding the line performance were obtained from the window analysis using the traditional DEA models and SBM. The main difference between the two techniques is that the window analysis using the CCR and BCC models identifies the causes of inefficiency; managerial or scale, while the SBM calculates the overall inefficiency and provides excess input slacks and outputs shortage. In conclusion, the proposed window analysis shall provide valuable information to the decision-makers regarding the existing performance of the packaging operations, help identification of the main causes of the technical inefficiencies, and determine the required actions for efficiency improvement.

V. Conclusions

This research proposed a window analysis procedure for the efficiency evaluation from fuzzy input and output data for packaging operations over the year 2020. Three inputs were considered including the planned production quantity, defect quantity, and idle time, while the output was the produced quantity for seven DMUs. The technical efficiency (TE) and pure technical efficiency (PTE) were calculated using the CCR and BCC models, respectively. Utilizing the TE and PTE, the scale efficiencies were assessed for both packaging lines. The results showed that for line PK2 TE and PTE are larger than their corresponding scores of line PK1 for all DMUs. Also, the PTIE of line PK1 is the main contributor to TIE, while for line PK2 the cause of TIE is contributed by PTIE and SIE. Finally, SBM was employed to assess the overall inefficiencies. The results revealed that the inputs' excess slacks averages for the PPQ, DQ, and IT were 59.579 (14.919), 1.328 (2.070), and 58.252 (12.849), for line PK1 (PK2), respectively. Moreover, line PK2 resulted in significant improvements and better utilization of PPQ and IT than line PK1. In conclusion, production management should perform frequent online detection and testing to prevent producing nonconforming packages, assess downtime trends, and effectively adjust the scale size according to the IRS and DRS results.

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Table 1. The collected data ($\times 10^4$).

Period	Packaging Line PK1*				Packaging Line PK2			
	Inputs			Output	Inputs			Output
	PPQ (units)	DQ (units)	IT (units)	APQ (units)	PPQ (units)	DQ (units)	IT (units)	APQ (units)
January	769.23	8.54	184.61	576.08	753.82	9.84	144.00	599.98
February	661.53	5.13	133.11	523.30	492.34	4.07	72.85	415.42
March	800.00	6.29	70.63	723.08	769.27	12.39	64.53	692.35
April	676.92	7.26	69.66	600.00	830.80	17.20	152.03	661.57
May	584.61	3.45	57.70	523.46	723.09	8.52	83.79	630.78
June	596.15	4.33	7.21	584.61	753.90	11.57	19.20	723.13
July	788.46	8.45	149.23	630.78	707.89	10.03	66.89	630.97
August	507.69	5.03	41.13	461.53	630.77	9.55	175.07	446.15
September	346.15	4.47	3.22	338.46	634.62	4.82	122.10	507.69
October	546.15	6.23	155.38	384.53	246.15	6.74	8.65	230.77
November	846.15	6.80	115.43	723.92	659.23	10.53	2.54	646.16
December	530.76	5.91	47.70	477.14	530.77	6.16	78.46	446.15

* PPQ: Planned production quantity; DQ: Defect quantity; IT: Idle time; APQ: actual produced quantity.

Table 2. The estimated technical efficiency for both lines.

		Month												
PK	**DMU**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
1	1	0.764	0.807	0.922	0.904	1.00	1.00							**0.899**
	2		0.807	0.922	0.904	1.00	1.00	0.816						**0.908**
	3			0.922	0.904	1.00	1.00	0.816	0.927					**0.928**
	4				0.904	1.00	1.00	0.816	0.927	1.00				**0.941**
	5					1.00	1.00	0.816	0.927	1.00	0.718			**0.910**
	6						1.00	0.816	0.927	1.00	0.718	0.872		**0.889**
	7							0.862	1.00	1.00	0.746	1.00	0.959	**0.928**
	Av. *	**0.764**	**0.807**	**0.922**	**0.904**	**1.00**	**1.00**	**0.824**	**0.942**	**1.00**	**0.727**	**0.936**	**0.959**	**0.899**
2	1	0.986	0.918	0.906	1.00	1.00	1.00							**0.968**
	2		0.911	0.898	0.992	1.00	0.924	1.00						**0.954**
	3			0.898	0.992	1.00	0.924	1.00	1.00					**0.969**
	4				0.992	1.00	0.924	1.00	1.00	0.950				**0.978**
	5					1.00	0.924	1.00	1.00	0.950	0.968			**0.974**
	6						0.924	1.00	1.00	0.950	0.968	0.980		**0.970**
	7							1.00	1.00	0.948	0.966	0.980	1.00	**0.982**
	Av.	**0.986**	**0.914**	**0.901**	**0.994**	**1.00**	**0.936**	**1.00**	**1.00**	**0.950**	**0.967**	**0.980**	**1.00**	**0.969**

* Average

Table 3. The pure technical efficiency values for both lines.

		Month												
PK	**DMU**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**Average**
1	1	0.773	0.884	1.00	0.914	1.00	1.00							**0.929**
	2		0.884	1.00	0.914	1.00	1.00	0.842						**0.940**
	3			1.00	0.914	1.00	1.00	0.842	1.00					**0.959**
	4				0.975	1.00	1.00	1.00	0.928	1.00				**0.984**
	5					1.00	1.00	1.00	0.928	1.00	0.720			**0.941**
	6						1.00	0.861	0.928	1.00	0.720	1.00		**0.918**
	7							0.920	1.00	1.00	0.751	1.00	0.991	**0.944**
	Av. *	**0.773**	**0.884**	**1.00**	**0.929**	**1.00**	**1.00**	**0.912**	**0.957**	**1.00**	**0.730**	**1.00**	**0.991**	**0.931**
2	1	0.986	0.918	0.9060	1.00	1.00	1.00							**0.968**
	2		0.918	0.9053	1.00	1.00	1.00	1.00						**0.971**
	3			0.9053	1.00	1.00	1.00	1.00	1.00					**0.984**
	4				1.00	1.00	1.00	1.00	1.00	0.955				**0.993**
	5					1.00	1.00	1.00	1.00	0.955	1.00			**0.993**
	6						1.00	1.00	1.00	1.00	1.00	1.00		**1.00**
	7							1.00	1.00	0.950	1.00	1.00	1.00	**0.992**
	Av.	**0.986**	**0.918**	**0.906**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**0.965**	**1.00**	**1.00**	**1.00**	**0.981**

* Average

Table 4. The estimated scale efficiency values for both lines.

PK	DMU	Month												Average
		1	2	3	4	5	6	7	8	9	10	11	12	
1	1	0.988	0.913	0.922	0.989	1.00	1.00							**0.969**
	2		0.913	0.922	0.989	1.00	1.00	0.969						**0.965**
	3			0.922	0.989	1.00	1.00	0.969	0.927					**0.968**
	4				0.927	1.00	1.00	0.816	0.999	1.00				**0.957**
	5					1.00	1.00	0.816	0.999	1.00	1.00			**0.969**
	6						1.00	0.947	0.999	1.00	0.998	0.872		**0.969**
	7							1.00	1.00	1.00	1.00	1.00	1.00	**1.00**
	Av.	**0.988**	**0.913**	**0.922**	**0.973**	**1.00**	**1.00**	**0.919**	**0.985**	**1.00**	**0.999**	**0.936**	**1.00**	**0.970**
2	1	1.00	1.00	1.00	1.00	1.00	1.00							**1.00**
	2		0.992	0.992	0.992	1.00	0.924	1.00						**0.983**
	3			0.992	0.992	1.00	0.924	1.00	1.00					**0.985**
	4				0.992	1.00	0.924	1.00	1.00	0.995				**0.985**
	5					1.00	0.924	1.00	1.00	0.995	1.00			**0.986**
	6						0.924	1.00	1.00	0.950	0.968	0.980		**0.970**
	7							1.00	1.00	1.00	1.00	1.00	1.00	**1.00**
	Av.	**1.00**	**0.996**	**0.995**	**0.994**	**1.00**	**0.936**	**1.00**	**1.00**	**0.985**	**0.989**	**0.990**	**1.00**	**0.990**

Table 5. The estimated efficiency values using SBM for both lines.

PK	DMU	Month												Average
		1	2	3	4	5	6	7	8	9	10	11	12	
1	1	0.434	0.537	0.6330	0.541	1.00	1.00							0.691
	2		0.537	0.633	0.541	1.00	1.00	0.473						0.697
	3			0.633	0.541	1.00	1.00	0.473	0.581					0.705
	4				0.541	1.00	1.00	0.473	0.581	1.00				0.766
	5					1.00	1.00	0.473	0.581	1.00	0.402			0.743
	6						1.00	0.473	0.581	1.00	0.402	0.579		0.673
	7							0.615	0.615	0.615	0.615	0.615	0.615	0.615
	Av.	**0.434**	**0.537**	**0.633**	**0.541**	**1.00**	**1.00**	**0.497**	**0.588**	**0.904**	**0.473**	**0.597**	**0.615**	**0.651**
2	1	0.771	0.556	0.546	1.00	1.00	1.00							0.812
	2		0.487	0.480	0.781	1.00	0.633	1.00						0.730
	3			0.480	0.781	1.00	0.632	1.00	1.00					0.816
	4				0.781	1.00	0.632	1.00	1.00	0.728				0.857
	5					1.00	0.632	1.00	1.00	0.728	0.789			0.858
	6						0.632	1.00	1.00	0.728	0.789	0.691		0.807
	7							1.00	1.00	0.727	0.772	0.691	1.00	0.865
	Av.	**0.771**	**0.521**	**0.502**	**0.836**	**1.00**	**0.694**	**1.00**	**1.00**	**0.728**	**0.783**	**0.691**	**1.00**	**0.794**

Table 6. The estimated input excess and output shortage slacks for both lines.

Eff.	DMU	PK1 (Slack)				PK2 (Slack)				Difference (PK2-PK1)			
		PPQ	DQ	IT	APQ	PPQ	DQ	IT	APQ	ΔPPQ	ΔDQ	ΔIT	ΔAPQ
TE	**1**	0	0.848	57.76	0	0	1.533	14.586	0	0	0.685	-43.171	0
	2	0	0.843	54.44	0	0	2.653	21.695	0	0	1.810	-32.743	0
	3	0	1.008	43.02	0	0	1.532	15.240	0	0	0.525	-27.784	0
	4	0	0.933	33.66	0	0	0.436	10.553	0	0	-0.498	-23.107	0
	5	0	0.851	42.20	0	0	0.014	13.128	0	0	-0.836	-29.075	0
	6	0	0.946	57.50	0	0	1.585	13.403	0	0	0.639	-44.096	0
	7	0	0	33.98	0	0	1.571	6.271	0	0	1.571	-27.710	0
	Av.	0	0.776	46.08	0	0	1.332	13.554	0	0	0.556	-32.527	0
PTE	**1**	0	0.928	39.63	0.027	0	1.501	14.604	0	0	0.574	-25.029	-0.027
	2	0	0.885	34.45	0.027	0	1.470	13.515	0	0	0.586	-20.936	-0.027
	3	0	0.705	24.46	0	0	0.723	7.287	0	0	0.018	-17.175	0
	4	0	0.275	7.73	0	0	0	2.544	0	0	-0.275	-5.186	0
	5	0	0.052	23.47	0	0	0	2.545	0	0	-0.052	-20.920	0
	6	0	0.408	37.70	0	0	0	0.001	0	0	-0.408	-37.703	0
	7	0.58	0.35	25.32	0	0	0	2.821	0	-0.576	-0.350	-22.496	0
	Av.	**0**	**0.54**	**27.91**	**0.009**	**0**	**0.616**	**6.749**	**0**	**0**	**0.074**	**-21.158**	**-0.009**

Table 7. The estimated inefficiency values for both lines.

PK	DMU	TIE	PTIE	SIE	IRS	CRS	DRS
1	DMU1	0.1007	0.0715	0.0314	0	4	2
	DMU2	0.0920	0.0600	0.0347	0	3	3
	DMU3	0.0719	0.0406	0.0323	1	2	3
	DMU4	0.0589	0.0161	0.0431	0	4	2
	DMU5	0.0899	0.0587	0.0309	0	5	1
	DMU6	0.1111	0.0819	0.0306	0	4	2
	DMU7	0.0720	0.0563	0.0000	0	4	2
	Average	**0.0852**	**0.0550**	**0.0290**	**2.38%**	**61.90%**	**35.71%**
2	DMU1	0.0317	0.0316	0.0000	0	6	0
	DMU2	0.0460	0.0295	0.0167	0	2	4
	DMU3	0.0311	0.0158	0.0154	0	3	3
	DMU4	0.0224	0.0075	0.0150	1	3	2
	DMU5	0.0264	0.0075	0.0136	1	3	2
	DMU6	0.0297	0.0000	0.0297	1	2	3
	DMU7	0.0177	0.0083	0.0000	0	3	3
	Average	**0.0293**	**0.0143**	**0.0129**	**7.14%**	**52.38%**	**40.48%**

Table 8. The causes of lines' inefficiency.

PK	Measure	Month											
		1	2	3	4	5	6	7	8	9	10	11	12
1	TIE	0.236	0.193	0.078	0.096	0	0	0.176	0.058	0	0.273	0.064	0.041
	PTIE	0.227	0.116	0	0.071	0	0	0.089	0.043	0	0.270	0	0.009
	SIE	0.012	0.087	0.078	0.027	0	0	0.081	0.015	0	0.001	0.064	0
	Cause	PTE	PTE	SE	PTE	Efficient	Efficient	PTE	PTE	Efficient	PTE	SE	PTE
2	TIE	0.014	0.086	0.099	0.006	0	0.0637	0	0	0.0505	0.033	0.020	1.00
	PTIE	0.014	0.082	0.095	0	0	0	0	0	0.0350	0	0	1.00
	SIE	0	0.004	0.005	0.006	0	0.0637	0	0	0.015	0.01	0.010	1.00
	Cause	PTE	PTE	PTE	SE	Efficient	SE	Efficient	Efficient	PTE	SE	SE	

Table 9. The estimated slack values by SBM for both lines.

DMU	PK1 (Slack)				PK2 (Slack)				Difference (PK2-PK1)			
	PPQ	DQ	IT	APQ	PPQ	DQ	IT	APQ	ΔPPQ	ΔDQ	ΔIT	ΔAPQ
DMU1	72.904	1.548	71.356	0	18.099	2.033	16.065	0	-54.805	0.485	-55.290	0
DMU2	66.813	1.466	65.347	0	27.244	3.309	23.935	0	-39.569	1.842	-41.412	0
DMU3	51.670	1.527	50.144	0	16.544	2.522	14.022	0	-35.127	0.995	-36.122	0
DMU4	41.228	1.370	39.858	0	9.444	1.290	8.154	0	-31.784	-0.080	-31.704	0
DMU5	56.052	1.464	54.588	0	11.204	1.038	10.166	0	-44.848	-0.427	-44.422	0
DMU6	74.043	1.704	72.339	0	13.127	2.670	10.457	0	-60.916	0.966	-61.882	0
DMU7	54.345	0.214	54.132	0	8.775	1.632	7.144	0	-45.571	1.419	-46.988	0
Average	**59.579**	**1.328**	**58.252**	**0**	**14.919**	**2.070**	**12.849**	**0**	**-44.660**	**0.743**	**-45.403**	**0**