Neural Computing and Applications (2019) 31:3703–3717
https://doi.org/10.1007/s00521-017-3303-2

ORIGINAL ARTICLE

DEA window analysis for assessing efficiency of blistering process in a pharmaceutical industry

Abbas Al-Refaie[1] · Chien-Wei Wu[2] · Moaath Sawalheh[1]

Received: 15 February 2016 / Accepted: 27 December 2017 / Published online: 5 January 2018

Abstract

This research evaluates the efficiency of blistering lines over a 2-year period starting January 2013 till December 2014 using data envelopment analysis models. The planned production quantity in units, defect quantity in units, and idle time in units are selected as inputs. The actual produced quantity in units is the output measure. The data are then normalized using the min–max normalization. Six windows are formed, and then the technical, pure technical, and scale efficiency are calculated for three identical blistering machines lines, BL1, BL2, and BL3, in each year. Results showed significant reductions in technical (TIE), pure technical (PTIE) inefficiency, and scale inefficiency (SIE) scores in year 2014. For BL1, the average TIE, PTIE, and SIE are reduced from 0.1152 to 0.0477, 0.0751 to 0.0176, and 0.0429 to 0.0304, respectively. For BL2, the average TIE, PTIE, SIE are reduced from 0.0968 to 0.0282, 0.0514 to 0.0133, and 0.0486 to 0.0149, respectively. Finally, for BL3, the average TIE, PTIE, SIE are reduced from 0.0936 to 0.0527, 0.0396 to 0.0154, and 0.0556 to 0.0380, respectively. In practice, the sources of TIE are mainly failure to operate at most productive scale size (SIE) and/or the poor input utilization (PTIE). In conclusion, the research results provide valuable feedback on how to improve efficiency, utilize resources, and effectively manage production lines.

Keywords Window analysis · CCR · BCC · Inefficiency · DEA

1 Introduction

In pharmaceutical industry, packaging process of the vaccines and medicines is important to ensure the integrity and quality of these products throughout the distribution chain. One of the important packaging processes is blister packing, which is used for packing a number of products, such as tablets and capsules. Blister packing provides a barrier protection for shelf life requirements and provides also a degree of tamper resistance. The most important reason for introducing blister packaging technology is to offer patients a clearly marked individual dose that enables them to check whether they are taking the prescribed drugs on a given day. Continual assessment of the efficiency of blister packing process is crucially important for pharmaceutical companies to be competitive in Jordanian market.

Data envelopment analysis (DEA) has been employed to assess the performances of a number of homogeneous decision-making units (DMUs), which used multiple inputs to produce multiple outputs [1–3]. A wide range of business applications for efficiency evaluation can be found in [4–6]. Nevertheless, when a limited number of DMUs are available, 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]. Yang [14] developed an enhanced DEA model for decomposition of technical efficiency in banking. Řepková [15] assessed efficiency of the Czech banking sector employing DEA window analysis. Tavana et al. [16] employed a hybrid fuzzy MCDM method for measuring the performance of publicly held pharmaceutical companies. Al-Refaie et al. [17] employed DEA window analysis and Malmquist index to assess energy efficiency and productivity in Jordanian

✉ Chien-Wei Wu
cweiwu@ie.nthu.edu.tw

1 Department of Industrial Engineering, University of Jordan, Amman 11942, Jordan

2 Department of Industrial Engineering and Engineering Management, National Tsing Hua University, Hsinchu 30013, Taiwan

industrial sector. Banerjee [18] performed an empirical study to measure the efficiency of Indian pharmaceutical companies during recession period utilizing DEA techniques. Gascón et al. [19] measured the efficiency of large pharmaceutical companies. Rentala et al. [20] conducted a comparative analysis of transitory trips and post-trips periods and assessed institutional reforms and export efficiency of Indian pharmaceutical industry. In this research, a Jordanian pharmaceutical company aims at evaluating the efficiency of its three blistering packing lines, BL1, BL2, and BL3, and determining the sources of the inefficiency over a period January 2013 to December 2014 by DEA techniques. The aim is to guide production managers in decision-making process on how to improve productivity and better utilize the available resources, reduce inefficiency, and assess the need for technology introduction. The remainder of this paper is organized as follows. Section 2 presents DEA models. Section 3 presents data collection and analysis. Section 4 summarizes results and discussions. Finally, research conclusions are made in the last Sect. 5.

2 DEA models

DEA is a data-driven frontier analysis technique that floats a piecewise linear surface to rest on top of the empirical observations [21]. The most well-known DEA models were the CCR [1] and BCC [22] models. Consider a set of n DMUs. For DMU k, let $y_{rk}(r = 1,\ldots,s)$ denote the level of rth output, and $x_{ik}(i = 1,\ldots,m)$ the level of ith input. The CCR model is used to measure the technical efficiency of a specific DMU k as follows [23, 24]:

(CCR Model)

$$\text{Min}\ \theta \quad \text{s.t.} \tag{1a}$$

$$\theta x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1,\ldots,m \tag{1b}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \quad r = 1,\ldots,s \tag{1c}$$

$$\lambda_j \geq 0, \quad j = 1,\ldots,n \quad \theta\ \text{unrestricted in sign} \tag{1d}$$

The optimal θ denoted by $\theta*$ satisfies $0 \leq \theta* \leq 1$. If $\theta*$ equals to one, the DMU under measurement is technically efficient and lies on the efficiency frontier that is composed of the set of efficient units. The model above is often referred to as the input-oriented Charnes–Cooper–Rhodes (CCR) model under constant returns to scale (CRS) assumed, which means that a proportional increase in all inputs results in the same proportional increase in output. An input-oriented model seeks to minimize inputs while satisfying at least the given output levels. Similarly, when outputs will be maximized, one can obtain an output-oriented model when inputs are fixed at their current levels. As a result, the objective value (or score) of CCR is designated technical efficiency (TE), which reflects the firm's ability to obtain maximum output from a given set of inputs [25]. On the other hand, CRS means that when input increased by a factor α, the output increases by the same factor. That is, the size of operation of DMU is optimal. Increasing returns to scale (IRS) means that when input increased by a factor α, the output increases by more than α. Decreasing returns to scale (DRS) means that when input increases by a factor α, the output increases by less than α [26]. To take variable returns to scale (VRS) into account, the CCR model is extended to BCC model as follows:

$$\text{Min}\ \theta \quad \text{s.t.} \tag{2a}$$

$$\theta x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0, \quad i = 1,\ldots,m \tag{2b}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rk}, \quad r = 1,\ldots,s \tag{2c}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \tag{2d}$$

$$\lambda_j \geq 0, \quad j = 1,\ldots,n \quad \theta\ \text{unrestricted in sign} \tag{2e}$$

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. The BCC model measures the pure technical efficiency (PTE) which ignores the impact of the scale size by only comparing a DMU to a unit of similar scale [27]. The PTE measures how a DMU utilizes its sources under exogenous environments; a low PTE implies that the DMU inefficiently manages its resources. The use of the BCC model allows decomposition of TE score into PTE and scale efficiency (SE) scores, where the relationship between them is expressed as:

$$\text{SE} = \frac{\text{TE}}{\text{PTE}} \tag{3}$$

SE measures how the scale size affects efficiency. SE also provides the ability of the management to choose the optimum size of resources, in other words, to choose the production scale that will attain the expected level of production.

When using DEA, 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, the model may produce numerous relatively efficient units and decrease discriminating power. To resolve this difficulty, DEA window analysis [28] was introduced, in which the performance of a DMU in any period can be compared with its own performance in other periods as well as the performance of other DMUs. The window should be as small as possible to minimize the unfairness comparison over time, but still large enough to have a sufficient sample size [29]. Consider N DMUs ($n = 1,\ldots,N$) that all use r inputs to produce s outputs and are observed in $T(t = 1,\ldots,T)$ periods. Let DMU_n^t represent an observation n in period t with input vector X_n^t and output vector Y_n^t which are, respectively, given by:

$$X_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{rt} \end{bmatrix}, \tag{4}$$

$$Y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix} \tag{5}$$

If the window starts at time $k(1 \le k \le T)$ with width $w(1 \le w \le T - k)$, then the matrices of inputs and outputs are, respectively, denoted as follows:

$$X_{kw} = \begin{bmatrix} x_1^k & x_2^k & \cdots & x_N^k \\ x_1^{k+1} & x_2^{k+1} & \cdots & x_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \cdots & x_N^{k+w} \end{bmatrix}, \tag{6}$$

$$Y_{kw} = \begin{bmatrix} y_1^k & y_2^k & \cdots & y_N^k \\ y_1^{k+1} & y_2^{k+1} & \cdots & y_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \cdots & y_N^{k+w} \end{bmatrix} \tag{7}$$

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

3 Data collection and analysis

In this study, three blistering packing lines; BL1, BL2, and BL3, are considered. The data are obtained from the production reports over a period of 2 years (January 2013 to December 2014). The replacement of BL1 by NBL1 took place at the end of year 2013. In DEA analysis, the planned production quantity in units (PPQ), defect quantity in units (DQ), and idle time in units (IT) are selected as inputs. The actual produced quantity in units (APQ) is the output measure. The data are then normalized using the min–max normalization with a range 0.1–0.9 [30]:

$$X_N = 0.1 + \frac{0.8(X - X_{\min})}{(X_{\max} - X_{\min})}, \tag{8}$$

where X_N denotes the normalized value of the input or the output data, X denotes the original value of the data, while the $X_{\max}$ and $X_{\min}$ denote the maximum and the minimum original values of the data. Table 1 provides the inputs and output data for blistering lines BL1 and NBL1 during January 2013 to December 2014. Similar data are collected for BL2 and BL3. The basic concept in window analysis is the consideration of each blistering line as a different one in each of the months listed at the top of the table in order 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.

3.1 Analysis of technical efficiency

Table 2 presents the TE scores for BL1 during years 2013 and 2014. For instance, the first row (1–6) extends from January 2013 to June of the same year for a window length of 6 months that is exhibited in the first row. The next row (2–7) starts in February and extends to July, for another window, and so on. Cooper et al. [31] determined the number of windows and the number of data points as follows:

$$w = k - p + 1, \tag{9}$$

$$\mathrm{dl} = n \times p \times w, \tag{10}$$

where w is the number of windows, k is the number of periods, p is the length of window, dl is number of “different” lines, and n is the number of the production lines. In this research, the number of windows is $7(= 12 - 6 + 1)$, and dl is $126(= 3 \times 6 \times 7)$. The TE scores, which measure inefficiencies due to input/output configuration as well as the size of operation, are calculated using CCR model. Further, the rows can be used to examine trends that occur in each window. The columns are used to examine stability properties. From Table 2, it is noted that:

- The average efficiency values listed in each column show stable performance, because the differences between the efficiency averages in each month are negligible. For example, all the efficiency averages are equal to one in June.
- For BL1 in year 2013, the coefficient of variation (CV) values listed in all of the seven windows (rows) are larger than 5%, which means that the dispersion is significant, and thereby a trend is observed in the efficiencies of the same window. Contrary to NBL1 in year 2014, most of the CV values are less than 5% that indicates lack of trend in most windows.

Table 1 Inputs and output data for BL1 and NBL1 during January 2013 to December 2014

Period	Blistering	Original data				Normalized data			
		Inputs			Output	Inputs			Output
	Line	PPQ (units)	DQ (units)	IT (units)	APQ (units)	PPQ (units)	DQ (units)	IT (units)	APQ (units)
Jan.	BL1	10,000,000	111,000	2,400,000	7,400,000	0.7974	0.3960	0.9000	0.6333
Feb.		8,600,000	66,640	1,730,300	6,800,000	0.6538	0.1974	0.6737	0.5606
Mar.		10,400,000	81,780	918,200	9,400,000	0.8385	0.2652	0.3992	0.8758
Apr.		8,800,000	94,380	905,600	7,800,000	0.6744	0.3216	0.3949	0.6818
May		7,600,000	44,880	750,000	6,800,000	0.5513	0.1000	0.3423	0.5606
Jun.		7,750,000	56,240	93,700	7,600,000	0.5667	0.1509	0.1205	0.6576
Jul.		10,250,000	109,880	1,940,100	8,200,000	0.8231	0.3910	0.7446	0.7303
Aug.		6,600,000	65,400	534,600	6,000,000	0.4487	0.1919	0.2695	0.4636
Sep.		4,500,000	58,080	41,900	4,400,000	0.2333	0.1591	0.1030	0.2697
Oct.		7,100,000	81,000	2,020,000	5,000,000	0.5000	0.2617	0.7716	0.3424
Nov.		11,000,000	88,360	1,500,600	9,400,000	0.9000	0.2946	0.5960	0.8758
Dec.		6,900,000	76,880	620,120	6,200,000	0.4795	0.2432	0.2984	0.4879
Jan.	NBL1	5,300,000	28,518	871,480	4,400,000	0.4453	0.1624	0.4546	0.4273
Feb.		5,900,000	33,244	1,266,750	4,600,000	0.4915	0.1789	0.6172	0.4455
Mar.		5,000,000	34,726	765,270	4,200,000	0.4222	0.1841	0.4109	0.4091
Apr.		5,100,000	61,366	1,038,630	4,000,000	0.4299	0.2771	0.5233	0.3909
May		3,300,000	40,143	459,850	2,800,000	0.2911	0.2030	0.2853	0.2818
Jun.		6,500,000	86,535	1,013,460	5,400,000	0.5378	0.3650	0.5130	0.5182
Jul.		4,600,000	41,705	558,290	4,000,000	0.3913	0.2085	0.3258	0.3909
Aug.		8,500,000	57,584	1,442,410	7,000,000	0.6919	0.2639	0.6894	0.6636
Sep.		8,000,000	59,248	1,340,750	6,600,000	0.6534	0.2697	0.6476	0.6273
Oct.		5,900,000	38,083	261,900	5,600,000	0.4915	0.1958	0.2039	0.5364
Nov.		11,200,000	135,142	1,464,000	9,600,000	0.9000	0.5347	0.6983	0.9000
Dec.		4,700,000	52,890	47,100	4,600,000	0.3990	0.2475	0.1155	0.4455

PPQ planned production quantity, *DQ* defect quantity, *IT* idle time, *APQ* actual produced quantity

- The average TE values are less than one in all windows for both BL1 and NBL1, and thereby they are concluded inefficient in all windows. However, BL1 is found efficient in Months May and June, while NBL1 is only found efficient in January and December Table 3 displays the technical inefficiency (TIE) for BL1 and NBL1. To analyze the sources for inefficiency, the projection onto the efficient frontier is performed. Table 4 presents the projection onto the efficient frontier for the maximum and minimum TE values for BL1 and NBL1 during years 2013 and 2014. For BL1, the fourth window (4–9) corresponds to the largest TE average of 0.9204 (TIE = 0.0796). For this window, the following efficiencies are observed 0.8713, 1.00, 1.00, 0.7646, 0.8904, and 0.9961 for the first period till the sixth period, respectively. For the TE in April (= 0.8713) to become efficient, the planned production quantity in units (PPQ), defect quantity in units (DQ), and idle time in units (IT) should be decreased by 12.88, 51.35, and 68.36%, respectively. For months May and June, the TE is equal to one; hence, no reductions in the inputs are needed. For the TE (= 0.7646), the PPQ, DQ, and IT should be decreased by 23.54, 57.14, and 82.03%, respectively. For the fifth period (August) with the average TE of 0.8904, the PPQ, DQ, and IT should be decreased by 12.88, 51.35, and 68.36%, respectively. Finally, for the sixth period (September, TE = 0.9961) the DQ and IT should be decreased by 61.10 and 52.02%, respectively. Further, the smallest average TE (= 0.8466) corresponds to window (6–11). For this window, the TIE equals 0.1543. In order to reduce TIE, the efficiency values are analyzed and are found equal to 1.00, 0.7646, 0.8904, 0.9961, 0.5902, and 0.8385 for months June–November, respectively. In Table 4, the TE (= 0.5902), for example, can become efficient when

Table 2 TE values for BL1 and NBL1

BL1	1	2	3	4	5	6	7	8	9	10	11	12	Av.	STD	CV
(1–6)	0.6844	0.7389	0.9001	0.8713	1.0000	1.0000							0.8658	0.1313	0.1517
(2–7)		0.7389	0.9001	0.8713	1.0000	1.0000	0.7646						0.8791	0.1118	0.1272
(3–8)			0.9001	0.8713	1.0000	1.0000	0.7646	0.8904					0.9044	0.0885	0.0978
(4–9)				0.8713	1.0000	1.0000	0.7646	0.8904	0.9961				0.9204	0.0959	0.1042
(5–10)					1.0000	1.0000	0.7646	0.8904	0.9961	0.5902			0.8735	0.1670	0.1912
(6–11)						1.0000	0.7646	0.8904	0.9961	0.5902	0.8385		0.8466	0.1551	0.1832
(7–12)							0.8401	1.0000	1.0000	0.6344	1.0000	0.9494	0.9040	0.1459	0.1614
Average	0.6844	0.7389	0.9001	0.8713	1.0000	1.0000	0.7772	0.9123	0.9970	0.6049	0.9193	0.9494	0.8629	0.1319	0.1528
NBL1	1	2	3	4	5	6	7	8	9	10	11	12	Av.	STD	CV
(1–6)	1.0000	0.9464	1.0000	0.9384	0.9988	1.0000							0.9806	0.0297	0.0303
(2–7)		1.0000	1.0000	0.9104	0.9690	0.9647	1.0000						0.9740	0.0352	0.0361
(3–8)			0.9955	0.9104	0.9690	0.9647	1.0000	1.0000					0.9733	0.0346	0.0355
(4–9)				0.9104	0.9690	0.9647	1.0000	1.0000	0.9925				0.9728	0.0342	0.0352
(5–10)					0.8869	0.8830	0.9153	0.9179	0.8798	1.0000			0.9138	0.0453	0.0496
(6–11)						0.8830	0.9153	0.9179	0.8798	1.0000	0.9163		0.9187	0.0434	0.0472
(7–12)							0.9027	0.9179	0.8785	1.0000	0.8981	1.0000	0.9329	0.0535	0.0574
Average	1.0000	0.9732	0.9985	0.9174	0.9586	0.9433	0.9556	0.9507	0.9076	1.0000	0.9072	1.0000	0.9593	0.0359	0.0374

Av. average, *STD* standard deviation, *CV* coefficient of variation

Table 3 TIE and PTIE values over years 2013 and 2014

Year	Window	TIE			PTIE			SIE		
		BL1	BL2	BL3	BL1	BL2	BL3	BL1	BL2	BL3
2013	(1–6)	0.1342	0.0831	0.1036	0.0943	0.0724	0.0307	0.0449	0.0117	0.0742
	(2–7)	0.1209	0.0656	0.1155	0.0789	0.0543	0.0477	0.0469	0.0123	0.0695
	(3–8)	0.0956	0.1196	0.1120	0.0527	0.0358	0.0477	0.0446	0.0857	0.0660
	(4–9)	0.0796	0.1101	0.0944	0.0236	0.0296	0.0577	0.0566	0.0822	0.0397
	(5–10)	0.1265	0.0932	0.1015	0.0855	0.0549	0.0250	0.0417	0.0438	0.0776
	(6–11)	0.1534	0.0952	0.0624	0.1139	0.0596	0.0413	0.0428	0.0409	0.0223
	(7–12)	0.0960	0.1110	0.0661	0.0765	0.0532	0.0273	0.0225	0.0634	0.0399
	Average	0.1152	0.0968	0.0936	0.0751	0.0514	0.0396	0.0429	0.0486	0.0556
2014	(1–6)	0.0194	0.0347	0.0471	0.0103	0.0297	0.0230	0.0091	0.0050	0.0250
	(2–7)	0.0260	0.0367	0.0481	0.0149	0.0277	0.0230	0.0111	0.0090	0.0260
	(3–8)	0.0267	0.0295	0.0538	0.0168	0.0148	0.0101	0.0100	0.0147	0.0448
	(4–9)	0.0272	0.0225	0.0632	0.0172	0.0068	0.0193	0.0101	0.0158	0.0450
	(5–10)	0.0862	0.0252	0.0629	0.0296	0.0068	0.0106	0.0574	0.0184	0.0523
	(6–11)	0.0813	0.0206	0.0469	0.0264	0.0000	0.0106	0.0556	0.0206	0.0363
	(7–12)	0.0671	0.0284	0.0472	0.0082	0.0075	0.0110	0.0595	0.0209	0.0363
	Average	0.0477	0.0282	0.0527	0.0176	0.0133	0.0154	0.0304	0.0149	0.0380

TIE technical inefficiency, *PTIE* pure technical inefficiency, *SIE* scale inefficiency

only DQ is reduced by 37.53%. Similarly, Tables 2 and 3 also display the TE and TIE averages for NBL1 in all seven windows, respectively. In Table 2, the first window (1–6) corresponds to the largest TE average (= 0.9806). However, the fifth window (5–10) corresponds to the smallest TE average (= 0.9153). In Table 3, the corresponding TIE values are calculated 0.0194 and 0.0862. Table 4 displays the required actions to enhance the TE efficiency for this machine. Similarly, the averages of TE, TIE, and required improvements are conducted for BL2 and BL3. Tables 2 and 3 display the TE and TIE scores for machines BL2 and BL3 for all windows. Tables 5 and 6 summarize the required actions to enhance TE efficiency for BL2 and BL3, respectively.

- Observing the averages of TIE scores for the three machines listed in Table 3, it is noted that the largest average TIE score (= 0.1152) in year 2013 corresponds to BL1. Due to replacing this machine by NBL1 in year 2014, the TIE is reduced to 0.0477. Thus, the decision of replacement successfully improves the TE. Moreover, it is noted that the largest TIE score in year 2014 equals 0.0527, which corresponds to BL3. Figure 1 displays a comparison of TIE scores between years 2013 and 2014 for each machine. It is seen that the TIE scores in year 2014 are much less than 2013 due to some action taken to reduce the inputs: PPQ, DQ, and IT.

3.2 Analysis of pure technical efficiency

The TE is a measure of efficiency without scale consideration by comparing a DMU to other DMUs of the same size only. However, the pure technical efficiency (PTE) scores are computed under the assumption of VRS using BCC model. PTE reflects the managerial performance to organize the inputs in the production process. Table 7 displays the obtained PTE scores for BL1 and NBL1 in all windows.

Table 3 also displays the PTIE values in all windows. Clearly, none of the PTIE equals to zero in any window. Thus, the windows are PTE inefficient. In Table 7, it is noticed for BL1 that the windows (4–9) and (6–11) correspond to the largest and smallest PTE score averages of 0.9764 and 0.8886, respectively. In Table 3, the corresponding PTIE values are 0.0236 and 0.1139. Moreover, the largest and smallest PTE score averages for NBL1 are 0.9918 and 0.9704, which correspond to windows (7–12) and (5–10), respectively. The corresponding PTIE values are 0.0082 and 0.0296. To analyze the PTIE, the projection onto the efficient frontiers is carried out. Table 4 lists the reduction needed to enhance PTE, or reduce PTIE. For example, for window (4–9) for BL1 (PTE = 0.9764) in Table 7, the corresponding PTE scores are calculated and found equal to 0.9670, 1.00, 1.00, 1.00, 0.8914, and 1.00. For the first period (PTE = 0.9670) to become efficient, the PPQ should be decreased by 3.31%, DQ by 28.23%, and IT by 16.88%. Window number 6 has the lowest PTE average of 0.8861 for BL1. Similarly, the PTIE values are

Table 4 Projection onto the efficient frontiers for BL1

CCR model								BCC model							
2013				2014				2013				2014			
Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score	
Period I/O	Score Data	Period I/O	Score Dat a	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data
1	0.8713	2	0.7646	2	0.9464	1	0.8869	1	0.9670	2	0.8235	3	0.9507	2	0.8874
PPQ	− 12.88%	− 23.54%		− 5.54%		− 11.30%		− 3.31%		− 17.66%		− 4.94%		− 11.27%	
DQ	− 51.35%	− 57.14%		− 5.36%		− 49.33%		− 28.23%		− 49.16%		− 4.94%		− 46.22%	
IT	− 68.36%	− 82.03%		− 23.21%		− 62.45%		− 16.88%		− 62.54%		− 26.34%		− 59.12%	
APQ	0.00%	0.00%		0.00%		0.00%		0.00%		0.00%		0.00%		0.00%	
4	0.7646	3	0.8904	4	0.9384	2	0.8830	5	0.8914	3	0.8914			3	0.9634
PPQ	− 23.54%	− 10.96%		− 6.16%		− 11.71%		− 10.86%		− 10.86%				− 3.66%	
DQ	− 57.14%	− 44.56%		− 36.52%		− 48.18%		− 19.23%		− 19.23%				− 4.12%	
IT	− 82.03%	− 68.48%		− 24.97%		− 61.60%		− 58.54%		− 58.54%				− 23.14%	
APQ	0.00%	0.00%		0.00%		0.00%		0.00%		0.00%				0.00%	
5	0.8904	4	0.9961	5	0.9988	3	0.9153			5	0.6016			5	0.9715
PPQ	− 10.96%	0.00%		0.00%		− 8.46%				− 39.84%				− 2.86%	
DQ	− 44.56%	− 61.10%		− 37.53%		− 31.56%				− 39.84%				− 9.36%	
IT	− 68.48%	− 52.02%		0.00%		− 54.39%				− 86.19%				− 14.94%	
APQ	0.00%	0.00%		0.00%		0.00%				1.70%				0.00%	
6	0.9961	5	0.5902			4	0.9179								
PPQ	0.00%	− 40.99%				− 12.12%									
DQ	− 61.10%	− 69.98%				− 8.21%									
IT	− 52.02%	− 91.87%				− 63.41%									
APQ	0.00%	0.00%				0.00%									
		6	0.8385			5	0.8798								
		− 16.14%				− 12.03%									
		− 31.78%				− 15.10%									
		− 73.07%				− 63.18%									
		0.00%				0.00%									

PPQ planned production quantity, *DQ* defect quantity, *IT* idle time, *APQ* actual produced quantity

Table 5 Projection onto the efficient frontiers for BL2

CCR model								BCC model							
2013				2014				2013				2014			
Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score	
Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data
2	0.9203	1	0.9203	1	0.9407	1	0.9225	1	0.8317	1	0.8308	4	1.0000	1	0.9868
PPQ	− 7.97%	− 7.97%		− 5.92%		− 7.75%		− 16.83%		− 16.93%		0.00%		− 1.32%	
DQ	− 12.83%	− 12.83%		− 5.92%		− 32.33%		− 48.88%		− 16.93%		− 12.32%		− 6.85%	
IT	− 56.07%	− 56.07%		− 52.72%		− 65.41%		− 60.04%		− 59.21%		− 32.94%		− 23.17%	
APQ	0.00%	0.00%		0.00%		0.00%		0.00%		0.00%		4.26%		0.00%	
3	0.7856	2	0.7856	4	0.9528	2	0.9109	4	0.9908	3	0.9305			2	0.9232
PPQ	− 21.45%	− 21.45%		− 4.71%		− 8.91%		− 0.93%		− 6.94%				− 7.68%	
DQ	− 43.45%	− 43.45%		− 4.71%		− 32.56%		− 16.30%		− 14.76%				− 31.62%	
IT	− 79.65%	− 79.65%		− 42.98%		− 69.13%		− 4.12%		− 47.16%				− 64.70%	
APQ	0.00%	0.00%		0.00%		0.00%		0.00%		0.00%				0.00%	
4	0.9685	5	0.9404	5	0.9828	4	0.9715			4	0.8041			3	0.9116
PPQ	− 3.16%	− 5.97%		− 1.73%		− 2.85%				− 19.60%				− 8.84%	
DQ	− 3.16%	− 5.97%		− 1.73%		− 29.31%				− 46.11%				− 31.86%	
IT	− 10.63%	− 39.21%		− 15.30%		− 44.95%				− 70.88%				− 68.50%	
APQ	0.00%	0.00%		0.00%		0.00%				0.00%				0.00%	
6	0.9318	6	0.6361			5	0.9748								
PPQ	− 6.83%	− 36.39%				− 6.15%									
DQ	− 6.83%	− 36.85%				− 2.51%									
IT	− 42.35%	− 89.87%				− 55.67%									
APQ	0.00%	0.00%				0.00%									

PPQ planned production quantity, *DQ* defect quantity, *IT* idle time, *APQ* actual produced quantity

Table 6 Projection onto the efficient frontiers for BL3

CCR model								BCC model							
2013				2014				2013				2014			
Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score		Largest TE Score		Smallest TE Score	
Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data	Period I/O	Score Data
2	0.8955	1	0.7930	1	0.9134	1	0.9767	4	0.8503	5	0.8680	3	0.9553	2	0.9067
PPQ	− 10.45%	− 20.70%		− 8.64%		− 2.35%		− 14.97%		− 13.19%		− 4.46%		− 9.34%	
DQ	− 10.45%	− 33.18%		− 43.30%		− 60.71%		− 28.66%		− 64.28%		− 47.63%		− 43.51%	
IT	− 43.45%	− 76.66%		− 57.14%		− 24.91%		− 55.19%		− 54.43%		− 58.00%		− 58.64%	
APQ	0.00%	0.00%		0.00%		0.00%		0.00%		0.00%		11.41%		0.00%	
3	0.8120	2	0.8600	2	0.9494	2	0.8374			6	0.8457	5	0.9843	5	0.9553
PPQ	− 18.81%	− 14.01%		− 5.05%		− 16.26%				− 15.43%		− 1.54%		− 4.46%	
DQ	− 36.91%	− 57.35%		− 50.18%		− 81.53%				− 71.39%		0.00%		− 47.63%	
IT	− 81.68%	− 59.11%		− 42.59%		− 71.69%				− 57.74%		− 12.94%		− 58.00%	
APQ	0.00%	0.00%		0.00%		0.00%				0.00%		0.00%		11.41%	
4	0.9634	5	0.8405	4	0.9438	3	0.9134								
PPQ	− 3.66%		− 15.95%	− 5.62%		− 8.64%									
DQ	− 26.66%		− 57.91%	− 24.70%		− 43.30%									
IT	− 51.30%		− 64.51%	− 44.68%		− 57.14%									
APQ	0.00%		0.00%	0.00%		0.00%									
5	0.9549	6	0.8135	5	0.9786	4	0.9494								
PPQ	− 4.51%		− 18.65%	− 2.14%		− 5.05%									
DQ	− 11.57%		− 64.99%	− 52.08%		− 50.18%									
IT	− 59.11%		− 68.54%	− 19.71%		− 42.59%									
APQ	0.00%		0.00%	0.00%		0.00%									
				6	0.9331	6	0.9438								
				− 6.68%		− 5.62%									
				− 78.73%		− 24.70%									
				− 41.56%		− 44.68%									
				0.00%		0.00%									

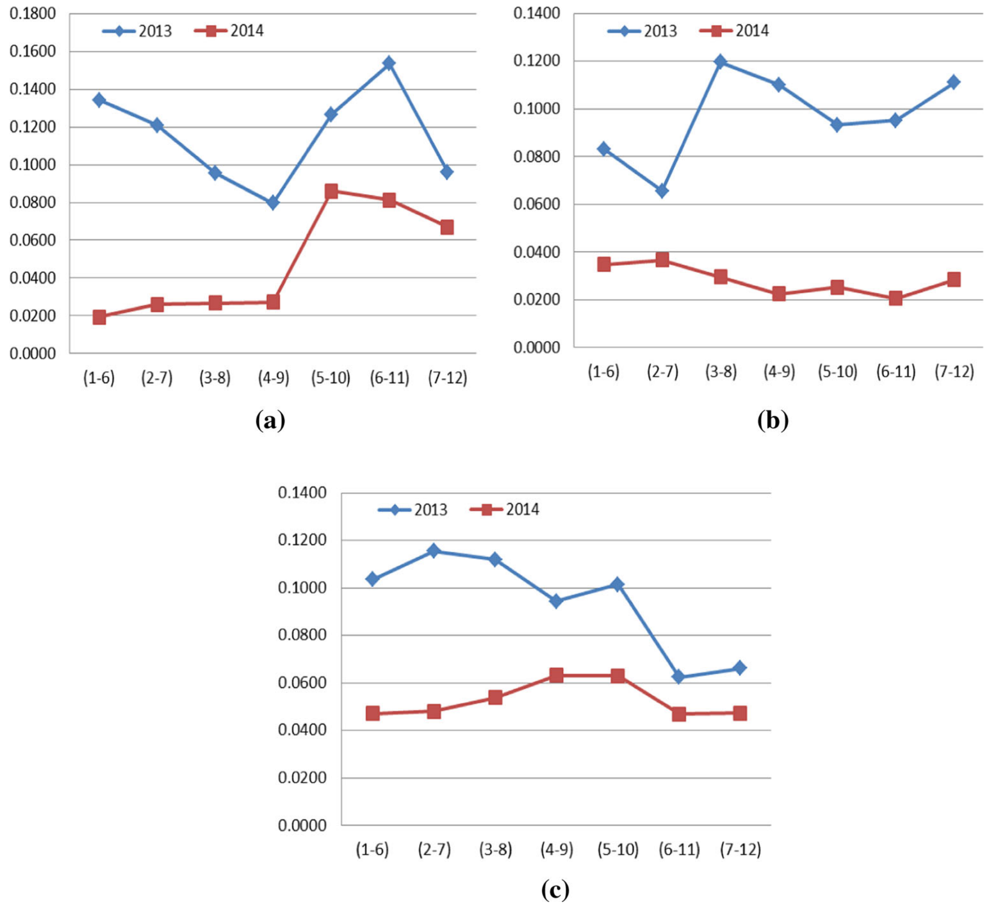

Fig. 1 Comparison of TIE values for each machine. **a** BL1. **b** BL2. **c** BL3

calculated for BL2 and BL3. The results are also shown in Table 3. In Table 3, the average of PTIE for BL2 is reduced from 0.0514 to 0.0154. Similarly, for BL3, the average of PTIE is reduced from 0.0396 to 0.0154. To obtain further improvements, Tables 5 and 6 show the actions needed to improve the PTE scores for BL2 and BL3 in year 2014, respectively.

3.3 Analysis of scale efficiency

Once the TE scores and PTE scores are obtained, the scale efficiency (SE) scores are calculated as TE divided by PTE for each window. If the score of TE equals the score of PTE, then the SE score equals one. This means that the size of operation is optimal. Otherwise, returns to scale analysis is required to determine whether operations of blistering lines need expansion or reduction in their sizes. When a blistering line has a small size of operation, that is increasing returns to scale (IRS), then the blistering line will need to plan for expansion. If the majority of inefficiency is due to the large size of operations, that is decreasing returns to scale (DRS), then the blistering line will need to plan for reduction.

Table 8 displays the SE values for BL1 and NBL1 for all windows, where the average SE values for BL1 and NBL1 are found equal to 0.9525 and 0.9726, respectively. Moreover, it is noted that the largest SE values correspond to windows (7–12) and (1–6) of 0.9775 and 0.9909 for BL1 and NBL1, respectively. Moreover, the SE values for NBL1 are larger than their corresponding values for BL1 in all windows. Table 9 displays the percentages of CRS, DRS, and IRS for all machines, where it is found that BL1 has 33, 36, and 31.0% of CRS, DRS, and IRS, respectively. However, NBL1 is 40.5, 36, and 28.5% of CRS, DRS, and IRS, respectively. For NBL1, the percentage of optimal size (= 40.5%) is larger than BL1 (= 33%). Moreover, BL1 and NBL1 should reduce their operation sizes. For BL2, 36% of results have optimal size of operations while 47% of results have IRS. This means that BL2 should expand their operations. For BL3, the majority of results have IRS behavior, which means that BL3 should also expand their operations. For year 2014, the scale of operations is improved, but the majority of results (= 69%) for BL3 have IRS behavior, which indicates that BL3 should expand their operations again. Table 3 displays the scale inefficiency (SIE) in years 2013 and 2014. Clearly, the SIE is dropped in 2014. The average of SIE for BL1 is dropped

Table 7 DEA window analysis for PTE for BL1 and NBL1

BL1	1	2	3	4	5	6	7	8	9	10	11	12	Average	STD	CV
(1–6)	0.7058	0.8431	1.0000	0.8851	1.0000	1.0000							0.9057	0.1191	0.1316
(2–7)		0.8431	1.0000	0.8851	1.0000	1.0000	0.7985						0.9211	0.0906	0.0984
(3–8)			1.0000	0.8851	1.0000	1.0000	0.7985	1.0000					0.9473	0.0861	0.0909
(4–9)				0.9670	1.0000	1.0000	1.0000	0.8914	1.0000				0.9764	0.0437	0.0447
(5–10)					1.0000	1.0000	1.0000	0.8914	1.0000	0.5958			0.9145	0.1621	0.1772
(6–11)						1.0000	0.8235	0.8914	1.0000	0.6016	1.0000		0.8861	0.1574	0.1776
(7–12)							0.8991	1.0000	1.0000	0.6549	1.0000	0.9872	0.9235	0.1374	0.1487
Average	0.7058	0.8431	1.0000	0.9056	1.0000	1.0000	0.8866	0.9349	1.0000	0.6174	1.0000	0.9872	0.9067	0.1277	0.1408
NBL1	1	2	3	4	5	6	7	8	9	10	11	12	Average	STD	CV
(1–6)	1.0000	1.0000	1.0000	0.9385	1.0000	1.0000							0.9897	0.0251	0.0254
(2–7)		1.0000	1.0000	0.9104	1.0000	1.0000	1.0000						0.9851	0.0366	0.0372
(3–8)			1.0000	0.9104	1.0000	0.9886	1.0000	1.0000					0.9832	0.0360	0.0366
(4–9)				0.9104	1.0000	0.9886	1.0000	1.0000	0.9977				0.9828	0.0358	0.0364
(5–10)					1.0000	0.8874	0.9634	1.0000	0.9715	1.0000			0.9704	0.0438	0.0451
(6–11)						0.8907	1.0000	1.0000	0.9507	1.0000	1.0000		0.9736	0.0451	0.0464
(7–12)							1.0000	1.0000	0.9507	1.0000	1.0000	1.0000	0.9918	0.0201	0.0203
Average	1.0000	1.0000	1.0000	0.9174	1.0000	0.9592	0.9939	1.0000	0.9676	1.0000	1.0000	1.0000	0.9865	0.0259	0.0263

Table 8 DEA window analysis for SE

BL1	1	2	3	4	5	6	7	8	9	10	11	12	Average	STD	CV
(1–6)	0.9697	0.8763	0.9001	0.9844	1.0000	1.0000							0.9551	0.0535	0.0561
(2–7)		0.8763	0.9001	0.9844	1.0000	1.0000	0.9575						0.9531	0.0531	0.0557
(3–8)			0.9001	0.9844	1.0000	1.0000	0.9575	0.8904					0.9554	0.0492	0.0515
(4–9)				0.9010	1.0000	1.0000	0.7646	0.9988	0.9961				0.9434	0.0959	0.1017
(5–10)					1.0000	1.0000	0.7646	0.9988	0.9961	0.9905			0.9583	0.0950	0.0991
(6–11)						1.0000	0.9285	0.9988	0.9961	0.9811	0.8385		0.9572	0.0641	0.0670
(7–12)							0.9345	1.0000	1.0000	0.9688	1.0000	0.9618	0.9775	0.0272	0.0278
Average	0.9697	0.8763	0.9001	0.9635	1.0000	1.0000	0.8845	0.9774	0.9970	0.9801	0.9193	0.9618	0.9525	0.0454	0.0476
NBL1	1	2	3	4	5	6	7	8	9	10	11	12	Average	STD	CV
(1–6)	1.0000	0.9464	1.0000	0.9999	0.9988	1.0000							0.9909	0.0218	0.0220
(2–7)		1.0000	1.0000	1.0000	0.9690	0.9647	1.0000						0.9889	0.0172	0.0174
(3–8)			0.9955	1.0000	0.9690	0.9758	1.0000	1.0000					0.9900	0.0140	0.0141
(4–9)				1.0000	0.9690	0.9758	1.0000	1.0000	0.9948				0.9899	0.0139	0.0140
(5–10)					0.8869	0.9951	0.9501	0.9179	0.9056	1.0000			0.9426	0.0473	0.0502
(6–11)						0.9913	0.9153	0.9179	0.9254	1.0000	0.9163		0.9444	0.0400	0.0423
(7–12)							0.9027	0.9179	0.9240	1.0000	0.8981	1.0000	0.9405	0.0471	0.0501
Average	1.0000	0.9732	0.9985	1.0000	0.9586	0.9838	0.9614	0.9507	0.9375	1.0000	0.9072	1.0000	0.9726	0.0303	0.0312

Table 9 Returns to scale analysis

Machine	2013	2014
BL1	33% CRS	40.5% CRS
	36% DRS	31% DRS
	31% IRS	28.5% IRS
BL2	36% CRS	45% CRS
	17% DRS	16% DRS
	47% IRS	39% IRS
BL3	28.5% CRS	24% CRS
	28.5% DRS	7% DRS
	43% IRS	69% IRS

from 0.0429 to 0.0304, from 0.0486 to 0.0149 for BL2, and from 0.0556 to 0.0380 for BL3.

4 Results discussion and implications

Providing guidance on what can be achieved in the short and long terms is done by decomposing technical efficiency scores into pure technical efficiency and scale efficiency. The inefficiencies due to technical, pure technical, scale efficiencies, TIE, PTIE, and SIE, summarized in Table 3 will be used for determining the main contributor of inefficiency. Generally, the TIE can be caused by PTIE or SIE. For illustration, the main contributor of TIE for BL1 in the first window in 2013 (PTIE $= 0.1342$, SIE $= 0.0449$) is due to pure technical inefficiency. It is noticed that the PTIE is the main cause for PTE, except the fourth window (PTIE $= 0.0236$, SIE $= 0.0566$) is due to scale inefficiency. In 2014, the main contributor of TIE for NBL1 is due to PTIE, except windows (5–10) and (6–11) are due to SIE. Further, the main contributor of inefficiency for BL2 in 2013 is due to PTIE, whereas the main contributor of TIE for BL3 in 2013 is due to SIE. In 2014, the main contributor of inefficiency for BL2 and BL3 is due to SIE. In practice, when the majority of inefficiency is due to SIE, increasing/decreasing returns to scale, expanding/downsizing of the operations should be done to observe an efficiency gains. On the other hand, if the majority of inefficiency in the production machine is due to PTIE, management is encouraged to improve the utilization of the inputs and the resources.

Further, the monthly differences of the TE, PTE, and SE scores between years 2013 and 2014 for each machine are calculated and then shown in Fig. 2. For the TE, the differences are negative during months May, June, September, and November. This means that the TE scores in 2013 outperform their corresponding values in 2014. Nevertheless, the differences do not exceed 0.08. However, the TE differences in the other 8 months are positive and some differences reach 0.4. Overall, the yearly averages of TE (= 0.9593), PTE (= 0.9865), and SE (= 0.9726) in 2014 are larger than the averages of TE (= 0.8629), PTE (= 0.9067), and SE (= 0.9525) in 2013. Significant improvements are gained in the performance of BL2 and BL3 in some months in year 2014. Figure 2 can be also used to identify the source of inefficiency in year 2014. For example, the positive TE difference (= 0.395) for BL1 in October is caused by PTE. However, the negative TE differences of − 0.0775 for BL2 in February and − 0.02 for BL3 in November are mainly attributed by PTE and SE, respectively.

5 Conclusions

This research successfully evaluated the efficiency of three blistering lines over a two-year period from January 2013 till December 2014 using DEA techniques. Three inputs are selected for DEA analysis, including the planned production quantity in units, defect quantity in units, and idle time in units. While, the actual produced quantity in units is the output. The data are normalized using the min–max normalization. Six windows are formed, and then the technical, pure technical, and scale efficiency are calculated by the CCR and BCC models for blistering machines in each year. Projection onto the efficient frontiers for TE and PTE scores is employed to determine appropriate actions on window inputs as well as on scale size in years 2013 and 2014. Results showed significant reductions in inefficiency scores in year 2014. For BL1, the average TIE, PTIE, SIE are reduced from 0.1152 to 0.0477, 0.0751 to 0.0176, and 0.0429 to 0.0304, respectively. For BL2, the average TIE, PTIE, SIE are reduced from 0.0968 to 0.0282, 0.0514 to 0.0133, and 0.0486 to 0.0149, respectively. Finally, for BL3, the average TIE, PTIE, SIE are reduced from 0.0936 to 0.0527, 0.0396 to 0.0154, and 0.0556 to 0.0380, respectively. In practice, the sources of TIE are mainly failure to operate at most productive scale size (SIE) and/or the poor input utilization (PTIE). Thus, to improve the performance of the blistering lines, production management shall carry out leak testing more frequently for earlier detection of a leak before a large volume of faulty blisters are produced, monitoring and addressing downtime trends, applying quality circles to increase productivity, reviewing hiring policy, increasing the size of raw material orders when the behavior of returns to scale is IRS, and enhancing employee motivation. One of the limitations of this research is the lack of a higher number of observations. As a future research, it would be interesting to further expand the time span.

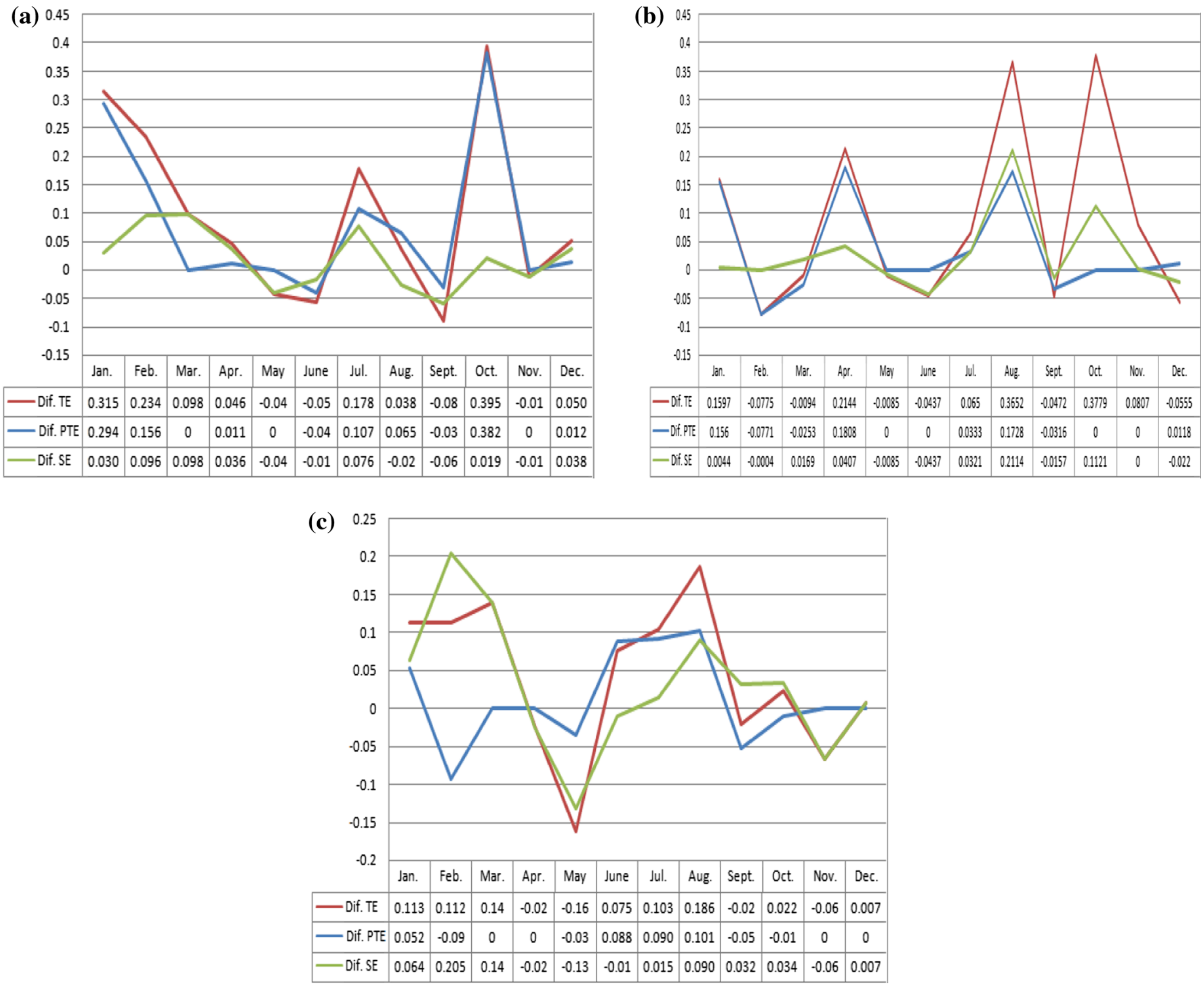

Fig. 2 Comparison between differences of TE, PTE, and SE versus year months. **a** BL1. **b** BL2. **c** BL3

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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