Available online at http://ijdea.srbiau.ac.ir

Int. J. Data Envelopment Analysis (ISSN 2345-458X)

Vol. 10, No. 2, Year 2022 Article ID IJDEA-00422, pages 13-30
Research Article

International Journal of Data Envelopment Analysis

Science and Research Branch (IAU)

Performance Monitoring over Time by Data Envelopment Analysis and Statistical Control Charts (A Real Maintenance Unit as Case Study)

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Received 3 February 2022, Accepted 1 May 2022

Abstract

Data envelopment analysis (DEA) is a well-known approach for measuring performance of units in the presence of multiple input and output variables. Statistical control charts, on the other hand, have been developed for monitoring performance over the time and for distinguishing between in-control and out-control states. Using advantages of these approaches in this paper, an integrated model is proposed for measuring and controlling performance of unit(s) over the time. A real maintenance unit and its data are used as a case study for better understanding of the proposed model.

Keywords: Data envelopment analysis; Control chart; Performance evaluation; EWMA; I-MR; Super-efficiency.

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1. Introduction

Measuring efficiency is one of the most important topics in the field of management, mainly used to identify efficient units. Data envelopment analysis (DEA) has been proposed in 1978 by [1] and extended by [2] in 1984 for measuring efficiency of decision-making units (DMUs). DEA is a non-parametric approach based on linear programming to compare the relative efficiency of DMUs in the presence of multiple inputs and outputs variables. DEA is utilized to solve many managerial problems such as DMUs ranking, targeting, and benchmarking [3-15].

Statistical process control (SPC), on the other hand, is a set of tools used for monitoring and improving quality of a process. Control chart, introduced by Walter Shewhart, is one of these tools, which is applied for controlling the process stability and identifying abnormal causes in the process variation [16]. In fact, Control charts are well-known tools for checking changes or variations in the processes [17].

There have been attempts in the literature to consider both SPC and DEA. As stated by [18-19], there is a conceptual link between performance assessment and control charts. They show that these two approaches can be used in a complementary manner. [20] used DEA to determine the parameters of $\bar{X}$ control charts. [21] applied *DEA* to solve a multi-objective model presented for designing $\bar{X}$ control charts. [22] proposed a multi-objective economic-statistical design of *np* control chart. This method is applied to find the pareto optimal solution and then a combined method based on *DEA* is developed to determine the most efficient design parameters. [23] illustrated a multi-objective model for the economic-statistical design of the C-control charts. This model consists of DEA and an improved version of the non-dominated sorting genetic algorithm. [24] considers an X-bar control chart design problem with multiple and often conflicting objectives. An integrated multi-objective algorithm is proposed for optimizing economical control chart design and two different multiple criteria decision making (MCDM) methods, including data envelopment analysis (DEA) and the technique for order of preference by similarity to ideal solution (TOPSIS), are used to reduce the number of Pareto optimal solutions to a manageable size.

2. PROPOSED MODEL

The proposed model integrates DEA and control charts to visualize DEA results. Clearly, this can help decision makers to detect abnormal states more quickly and more easily. The block diagram of the model is shown in Figure 1, which consists of two parts, phase I and phase II. In phase I, data are collected and the efficiencies of each DMU in a desired period are measured and are stabilized using a proper control chart. The needed parameters are also estimated in this phase. In phase II and based on the estimated parameters, another control chart is designed to detect abnormal states. The details of these two phases are as follows:

Phase I:

Step 1: Collecting Data

In DEA, a DMU is regarded as an entity responsible for converting inputs into outputs and whose performance has to be evaluated [25]. Therefore, for j^{th}DMU, a historical data set of input and output variables should be collected over the time. That is, for m input variables and s output variables, the data set would be:

$$S^j = \left\{ \left(x_{it}^j, y_{rt}^j \right) \middle| \begin{array}{l} i = 1,\ldots,m, \\ \mathrm{r} = 1,\ldots,\mathrm{s}, t = 1,\ldots,T \end{array} \right\}$$

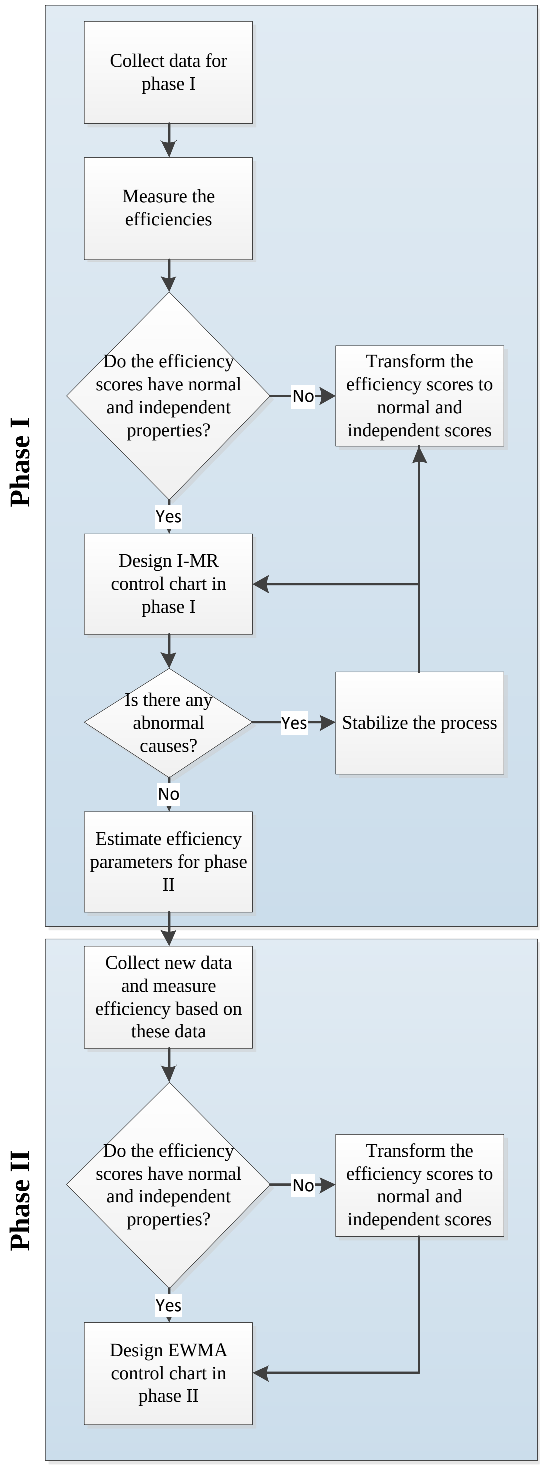

Figure 1. The block diagram of the model

where, x_{it}^{j} is i^{th} input of j^{th} DMU at t^{th} period of time and y_{rt}^{j} is r^{th} output of j^{th} DMU at t^{th} period of time.

Step 2: Measuring efficiencies

Basic DEA models are categorized into two main categories: efficiency models and ranking models. In this step and in order to discriminant the performances over the time more efficient, the ranking models are utilized. Therefore, supper efficiency DEA model is used for j^{th}DMU over the time ($t=1,...,T$) [26]:

$$Min\ \theta_{t_o}^{j} \qquad (1)$$

$$s.t\begin{cases}\sum_{\substack{t=1\\t\neq t_o}}^{T}\lambda_t x_{it}^{j}\le\theta_{t_o}^{j}x_{it_o}^{j} & i=1,\ 2,\ ...,\ m\\ \sum_{\substack{t=1\\t\neq t_o}}^{T}\lambda_t y_{rt}^{j}\ge y_{rt_o}^{j} & r=1,\ 2,\ ...,\ s\\ \lambda_t\ge 0\quad t\neq t_o & t=1,\ 2,\ ...,\ T\end{cases}$$

where, $\theta_{t_o}^{j}$ is super efficiency score for j^{th}DMU at $t_o^{\ th}$ period of time.

Step 3: Designing control chart

As there is one DEA score for each DMU in each period of time, it is better to use I-MR control chart [16]. This control chart composes of a Shewhart X-chart to detect shifts in the process mean and a Shewhart moving range (MR)-chart to detect changes in the process variability [27]. The MR statistic is defined as:

$$\sigma_{Z_t^j}^2=\sigma^2\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right] \quad (6)$$

The control limits for the X chart is:

$$\begin{cases}\mathrm{UCL}^j=\bar{\theta}^j+3\mathrm{S}_{\mathrm{MR}^j}\\ \mathrm{CL}^j=\bar{\theta}^j\\ \mathrm{LCL}^j=\bar{\theta}^j-3\mathrm{S}_{\mathrm{MR}^j}\end{cases} \qquad (3)$$

where, $\bar{\theta}^j=\frac{1}{T}\sum_{t=1}^{T}\theta_t^j$, $\overline{MR}^j=\frac{1}{T-1}\sum_{t=2}^{T-1}MR_t^j$ and $S_{MR^j}=\frac{\overline{MR}^j}{H}$, where $H=1.128$ is Hartley's constant used to convert mean moving range to a standard deviation [27]. There is only an upper limit for the moving range chart as:

$$UCL^j=3\overline{MR}^j \qquad (4)$$

Note that, Shewart control chart will not work well, if the quality characteristic does not follow normal distribution. In addition, this control chart will give misleading results in the form of too many false alarms, if there are correlations between data [16].

In order to deal with the non-normal data set, the original data set should be transformed to approximately normal data set and then the control charts are computed for this new data set. Moreover, to deal with auto correlated data set, the time series model has to be used to remove the autocorrelation, and then the control charts are computed for the residuals [16].

Step 4: Stabilizing the process

Each control chart displays a graphical view of the process stability or its instability. There are two types of variations in every process: special cause variations and common cause variations [30]. The control chart is developed to determine the existence of the special causes [27]. When special causes are not present in the process, the process is considered 'stable' otherwise it is classified as 'unstable' or 'out of statistical control' [31].

Thus, in this step, DEA scores, θ_t^j , that are outside the control chart limits are examined for potential special causes. These special causes are then eliminated and new control chart are evaluated. If these special causes could not be eliminated, they are considered as common causes.

In sum, during this step, the special causes are detected are eliminated and then the control limits are updated. Therefore, the process is stabilized and a clean data set representing in-control performances is obtained. The mean and variance parameters are also estimated based on this new data set. These parameters are used in phase II [16].

Phase II: Designing control chart

As the main purpose of designing control chart in phase II is detecting any special causes in the performance quickly, in this step the exponentially weighted moving average (EWMA) control chart is developed based on DEA scores. The EWMA control chart was introduced by [31] and its statistic is defined as [16]:

$$Z_t^j = \lambda\theta_t^j + (1-\lambda)Z_{t-1}^j \qquad (5)$$

where $0<\lambda<1$ is a constant and $Z_0^j = \bar{\theta}^j$.

Note that, the EWMA statistic can be viewed as a weighted average of all past and current scores, so it is insensitive to the non-normality assumption in data. In addition, it is an ideal control chart to monitor the individual scores. If θ_t^j s are independent variables with variance σ^2 , then the variance of Z_t^j will be [16]:

$$\sigma_{Z_t^j}^2 = \sigma^2\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right] \qquad (6)$$

Therefore, the EWMA control chart limits would be as follows:

$$UCL^j = \bar{\theta}^j + L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right]}$$

$$CL = \bar{\theta}^j \qquad (7)$$

$$LCL^j = \bar{\theta}^j - L\sigma\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right]}$$

where, L is the width of control limits and is usually obtained by Monte Carlo simulation. λ is a design parameter specified by the user? While small value of λ increases the charts sensitivity to small shifts in the performance mean, large value of λ increase the chart sensitivity to large shifts ([31-33]).

In order to examine the ability of the proposed model, in the next section a maintenance unit is selected and its performance over time are evaluated using the proposed model.

3. CASE STUDY

Nowadays, one of the foundations in industries and production units is to utilize machineries and equipment efficiently. For increasing productivity and efficiency, companies should pay special attention to efficiency, maintenance costs and machinery failures. Evaluating the performance of maintenance units using DEA has been done by some researchers such as [32-34].

In this section, a real maintenance unit is used for better understanding of the proposed model and its main features. In this case, the efficiency of this unit over time (months) is evaluated and controlled. According to experts' knowledge and historical data, the two inputs are the number of used pieces per month (x_{1t}^1) and working hours per month (x_{2t}^1). Three outputs, y_{1t}^1, y_{2t}^1, y_{3t}^1 are number of emergency activities per month (y_{1t}^1), number of preventive activities per month (y_{2t}^1) and number of workers per month (y_{3t}^1).

As aforementioned, in phase I of the proposed model, data are collected and the efficiencies of DMU in desired period of time are measured and stabilized using I-MR chart. The needed parameters are also estimated in this phase. In phase II and based on the estimated parameters, EWMA control chart is designed to detect abnormal states. For this DMU, these two phases are as follows:

Phase I:
Step 1: Collecting data

The input and output data set, $S^1=\left\{\left(x_{it}^1, y_{rt}^1\right) \middle| i=1,2, \mathrm{r}=1,\ldots,3, t=1,\ldots,36\right\}$ have been collected for 36 months ($t=1,\ldots,36$). The summary of these data is presented in Table 1.

Table 1: Summary of data collected in phase I

Statistic	x_{1t}^1	x_{2t}^1	y_{1t}^1	y_{2t}^1	y_{3t}^1
Max	968	96	2.585	0.755	0.076
Min	142	50	0.324	0.279	0.014
Mean	705	63	0.983	0.543	0.029

Table 2: Efficiency scores for 36 months in phase I

Month	Efficiency scores	Month	Efficiency scores
1	0.99	19	1.32
2	0.64	20	0.80
3	0.70	21	0.77
4	0.68	22	0.43
5	0.45	23	0.37
6	0.57	24	0.36
7	0.44	25	2.52
8	0.47	26	0.87
9	0.86	27	0.45
10	0.51	28	0.56
11	0.46	29	0.79
12	0.52	30	0.98
13	0.96	31	0.29
14	0.55	32	0.65
15	0.85	33	0.67
16	1.31	34	1.28
17	0.71	35	0.65
18	0.70	36	1.60

Step 2: Measuring efficiencies

In this step and to measure performances over time, the ranking model (model 1) are applied on S^1 and the obtained efficiency scores for 36 months are reported in Table 2.

Step 3: Designing control chart

In this step, the I-MR control chart is designed for stabilizing the process. However, the normality and autocorrelation assumption must be checked before handed. Figure 2 is depicted to show the autocorrelation function between the efficiencies in Table 2. Clearly, these data are independent. The normality assumption is checked using normal probability plot (Figure 3) and the result shows that the efficiency scores do not follow the normal distribution. Several transformation methods are used to normalize these data and based on the results, Box-Cox transformation method (Eq.8) is selected for normalization.

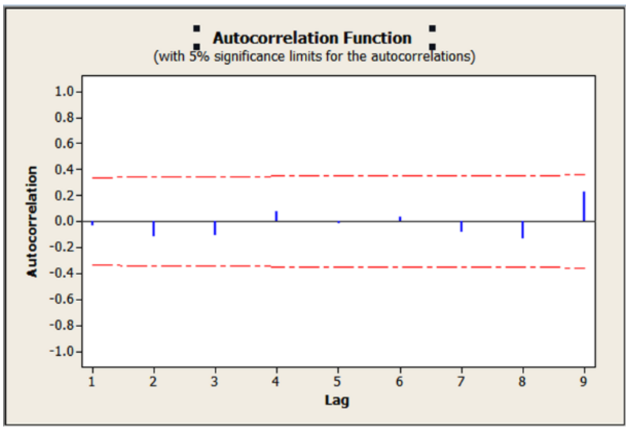

Figure 2. The autocorrelation function for efficiency scores in phase I

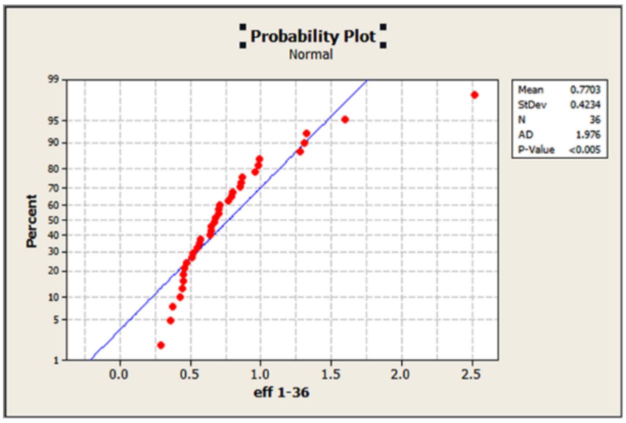

Figure 3. Normal probability plot for efficiency scores

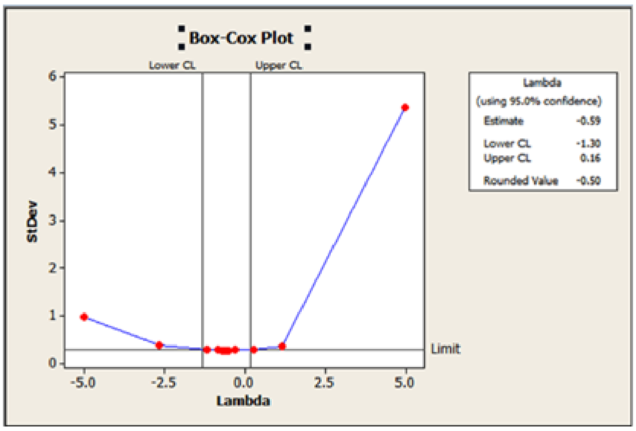

Figure 4. Box-Cox transformation

$$\theta'^{j}_{t} = \frac{\left(\left(\theta^{j}_{t}\right)^{Lambda} - 1\right)}{Lambda \times G^{Lambda-1}}, \quad Lambda \neq 0 \qquad (8)$$

where, G is Geometric mean of all the data. The optimum value of $Lambda$ is calculated via Minitab software, as it is shown in Figure 4. Using the optimum value of $Lambda$, $Lambda = -0.5$, the normalized efficiency scores for phase I are obtained (Table 3). Figure 5 checks the normality assumption of the transformed data.

Now, the I-MR control chart can be developed based on the normalized efficiency scores. This control chart is depicted in Figure 6. As it is shown in this figure, there is one out of control situation, which is going to be analyzed in the next step.

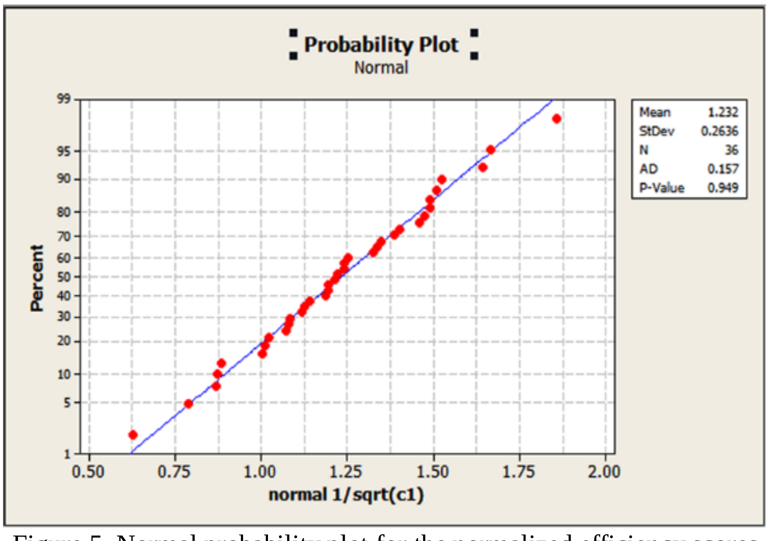

Figure 5. Normal probability plot for the normalized efficiency scores

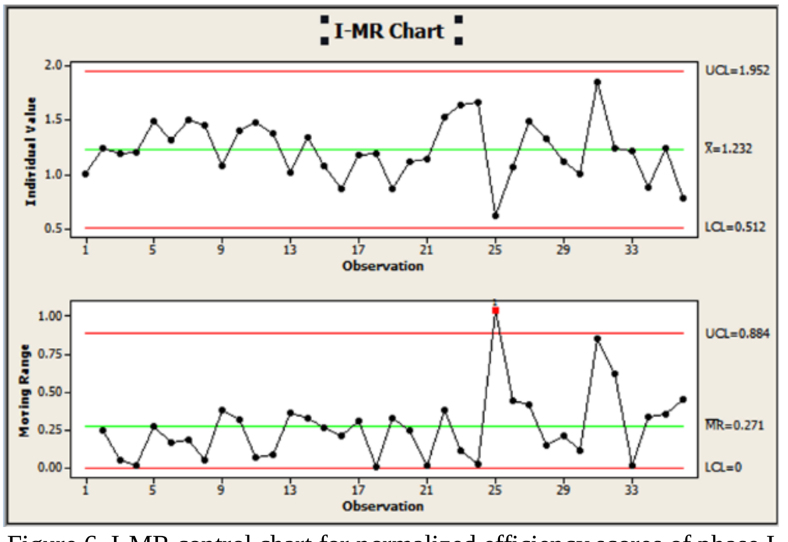

Figure 6. I-MR control chart for normalized efficiency scores of phase I

Table 3: Normalized efficiency scores

Month	Normalized Efficiency scores	Month	Normalized Efficiency scores
1	1.00504	19	0.87039
2	1.25000	20	1.11803
3	1.19523	21	1.13961
4	1.21268	22	1.52499
5	1.49071	23	1.64399
6	1.32453	24	1.66667
7	1.50756	25	0.62994
8	1.45865	26	1.07211
9	1.07833	27	1.49071
10	1.40028	28	1.33631
11	1.47442	29	1.12509
12	1.34840	30	1.01015
13	1.02062	31	1.85695
14	1.34840	32	1.24035
15	1.08465	33	1.22169
16	0.87370	34	0.88388
17	1.18678	35	1.24035
18	1.19523	36	0.79057

Step 4: Stabilizing the process

As mentioned before, in this step the out of control statuses are examined for the potential especial causes. As it is shown in Figure 6, the 25th month is out of control. The analyses mainly show that the corresponding efficiency scores could be eliminated because of existing special cause. The control limits are then updated and the new I-MR chart is plotted in Figure 7. In this new chart, it is observed that there is another out of control situation in 31st month. Similarly, the analyses show that the corresponding efficiency scores could be eliminated because of existing especial cause. The new I-MR chart is updated and is plotted in Figure 8. As it is shown in this figure, there is no out of control situation and the process could be considered as stable.

Once the I-MR control chart is in control, the mean and standard variation of efficiency scores could be estimated. These values are $\overline{\theta}^1 = 1.23$ and $\hat{\sigma} = 0.19$.

In the next phase, the EWMA control chart is developed to detect abnormal states, more efficient.

Phase II:

As the main purpose of designing control chart in phase II is detecting any special causes quickly, in this step the EWMA control chart is developed based on DEA scores. Hence, a new set of data for 36 months is collected for developing and accessing this control chart. A summary of these data are shown in Table 4. Efficiency scores for these months (DMUs) are also presented in Table 5.

Before developing EWMA control chart, the normality and autocorrelation assumption must be checked. Figure 9 is depicted to show the autocorrelation function between the efficiencies in Table 5. Clearly, these data are independent. The normality assumption is checked using normal probability plot (Figure 10). The result shows that the efficiency scores do not follow the normal distribution. Using Box-Cox, the optimum value of transfer parameter (Lambda) is -0.5 (Figure 11). The normalized efficiency scores for phase II using this parameter is shown in Table 6. Figure 12 shows that these new efficiency scores have normal distribution.

Table 4: Summary of data collected in phase II

Statistic	x_{1t}^1	x_{2t}^1	y_{1t}^1	y_{2t}^1	y_{3t}^1
Max	1001	104	2.2	1	0.1
Min	206	32	0.15	0.309	0.004
Mean	658	78	0.698	0.669	0.1

Table 5: Efficiency scores of DMUs in phase II

Month	Efficiency scores	Month	Efficiency scores
1	0.95	19	0.45
2	0.85	20	0.52
3	0.95	21	0.66
4	0.40	22	0.52
5	0.50	23	1.40
6	1.05	24	0.30
7	0.78	25	1.06
8	1.46	26	0.42
9	0.98	27	0.37
10	0.66	28	3.56
11	1.10	29	0.42
12	0.64	30	1.11

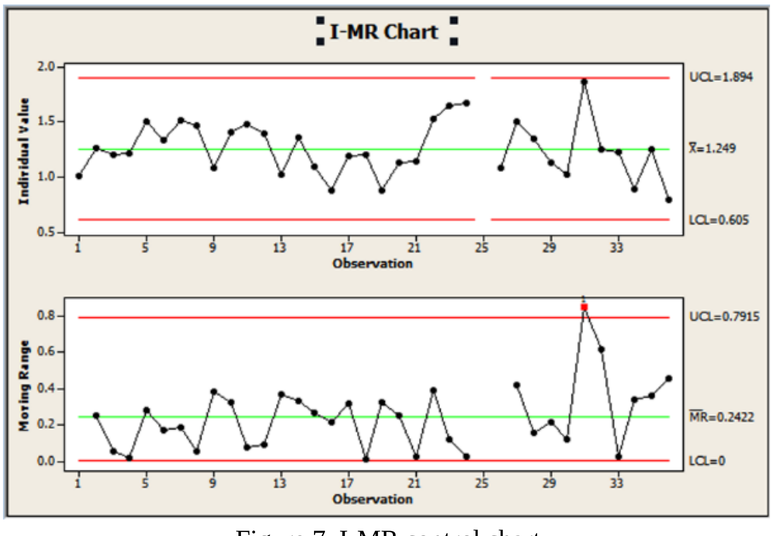

Figure 7. I-MR control chart

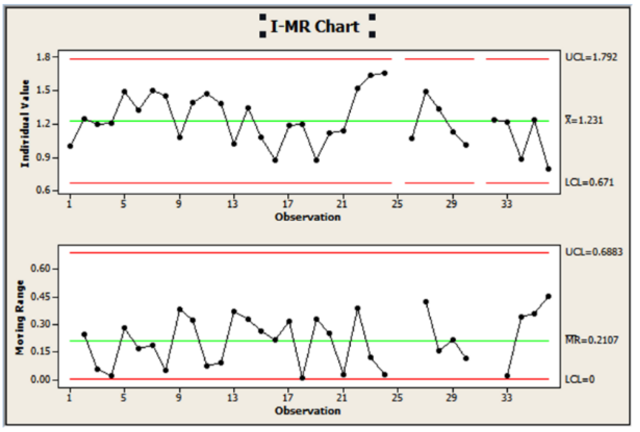

Figure 8. I-MR control chart

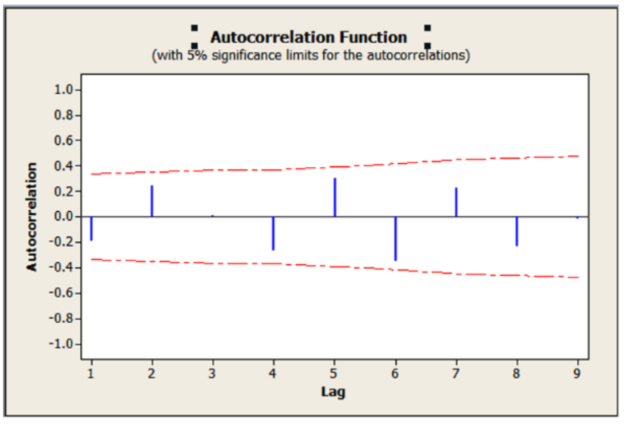

Figure 9. The autocorrelation function for efficiency scores in phase II

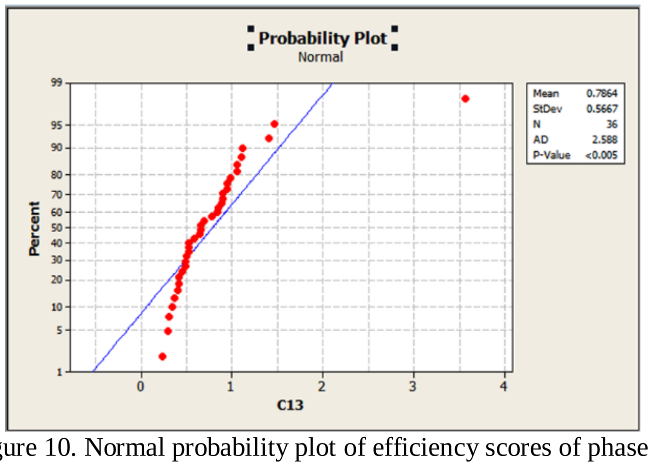

Figure 10. Normal probability plot of efficiency scores of phase II.

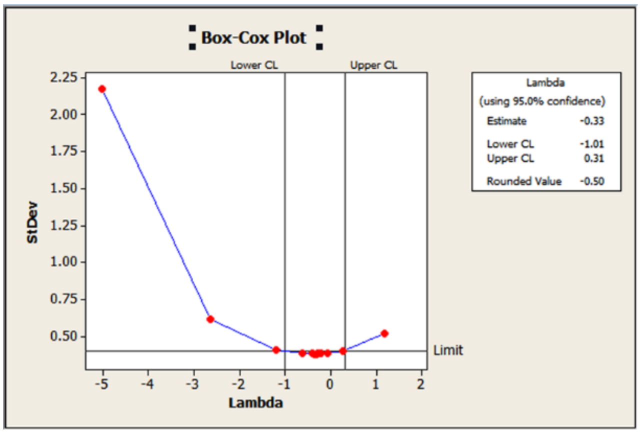

Figure 11. Box-Cox transformation

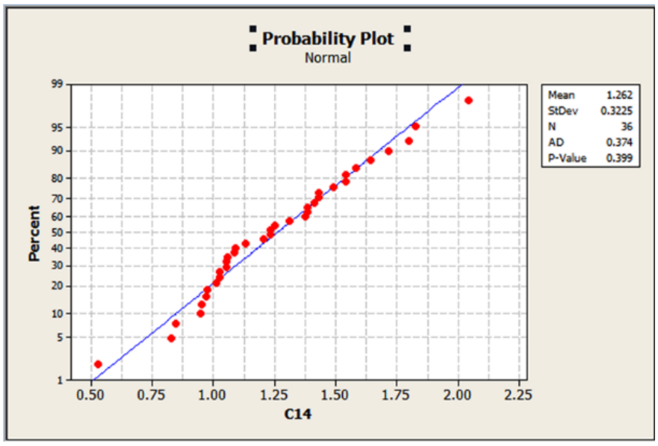

Figure 12. Normal probability plot of normalized efficiency scores in phase II

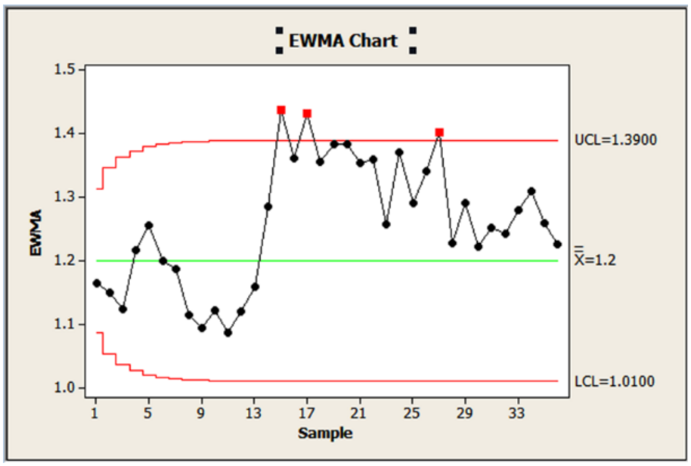

Figure 13. EWMA control chart for normalized efficiency scores of phase II

Table 6: Normalized efficiency scores of phases II

Month	Normalized Efficiency scores	Month	Normalized Efficiency scores
1	1.02598	19	1.49071
2	1.08465	20	1.38675
3	1.02598	21	1.23091
4	1.58114	22	1.38675
5	1.41421	23	0.84515
6	0.97590	24	1.82574
7	1.13228	25	0.97129
8	0.82761	26	1.54303
9	1.01015	27	1.64399
10	1.23091	28	0.53000
11	0.95346	29	1.54303
12	1.25000	30	1.94916
13	1.31306	31	1.37361
14	1.02598	32	1.20386
15	1.08465	33	1.42857
16	1.02598	34	0.42857
17	1.58114	35	1.05409
18	1.41421	36	1.09109

Using the estimated parameters in phase I, $\bar{\theta}^1 = 1.23$ and $\hat{\sigma} = 0.19$, the EWMA control chart settings are as follows:

$$UCL^1 = 1.23 + 0.19L\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right]}$$

$$CL^1 = 1.23 \qquad (9)$$

$$LCL^1 = 1.23 - 0.19L\sqrt{\left(\frac{\lambda}{2-\lambda}\right)\left[1-(1-\lambda)^{2t}\right]}$$

where, $L = 3$ and $\lambda = 0.2$.

Figure 13 shows the EWMA control chart based on these data. As it is shown in this figure, 15th, 17th, and 27th months are found as out of control state.

4. CONCLUSION

Nowadays, evaluating the performance has an important role in improving the efficiency and productivity organizations. Therefore, this paper presents an integrated model based on DEA and control charts for evaluating and controlling performance. This is done in two phases. In phase I, the performance of unit(s) over time is stabilized and in phase II, abnormal states are detected quickly. The I-MR control chart along with EWMA control chart is used in these two phases. A real case study consists of the performance values of a maintenance unit over time are used to evaluate the proposed model. This paper has some potential future work: Different control charts could be used and has to be studied on DEA results. Proposed methodology can be also developed for other organizations. Multi-stage control charts can be integrated with network DEA models, as well. Non-parametric control charts can also be used and results can be compared with the proposed model.

In sum, this paper integrates DEA, a well-known approach in performance assessment and SPC, a set of tools for controlling and improving. The advantages of this integration are DEA results could be monitored through control limits, applications of SPC could be extended by this integration especially in the DEA applications and this integration is an attractive area for future research.

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