International Journal of Applied Optimization Studies
Year 2018 Volume 1, Issue 1, pp. 59-70
www.ijaos.com

Statistical Process Control for Energy Consumption Monitoring in a cement factory Iranian Cement Factory

Amir-Mohammad Golmohammadi[a,*], Seyed Kamran Golestan[b]

[a]*Department of Industrial Engineering, University of Yazd, Yazd, Iran.*
[b]*Department of Management, London Business & Engineering School, London, UK.*

*Corresponding author email address: amir.m.golmohammadi@gmail.com

Abstract

In this paper, to assess the energy consumption monitoring in an Iranian cement factory, statistical process control (SPC) is deployed on clinker production process, which consumes more than 90% of the total energy consumption in considered cement factory. Within the process system boundary, clinker energy consumption records from February 2013 to January 2016, are retrieved focusing the monthly average index of thermal energy consumption placing the studied plant in the group of high energy consumption compared to the targeted values given in the ISIRI 7873 standard. The trial control limits for the existing process are established so that phase I of the process improvement could be started by using these control limits for process monitoring. The reasons for new assignable causes would then be identified and rectified until there are no more assignable causes and the process is said to be under statistical control. The process capability ratio value of -0.69 indicates inefficiency of the process with respect to the control limits. So, the process needs to be reviewed and the establishment of proper saving actions is necessary to improve energy efficiency.

Original Article:

Received 2018-06-10
Revised 2018-08-25
Accepted 2018-08-30

Keywords:

Statistical process control;
Cement industry;
I-MR control chart;
Energy monitoring;
ISIRI 7873 standard.

1. Introduction

During the last decade, there has been an increasingly intensive interest in assessing, measuring, and documenting the energy consumption and environmental performance (EP) of particularly energy-intensive industries (e.g. cement plants) (Von Bahr et al., 2003, Abu-Allaban, 2011, Afkhami et al., 2015, Nguyen and Hens, 2015).The problem of the sharp increases of energy consumption and carbon dioxide emissions in the cement industry can be addressed toan eco-industrial integrated framework(Liu et al., 2015). Cement industry is a potential anthropogenic source of air pollution. It is a major contributor to dust, nitrogen oxides, sulfur oxides (SOx), and carbon monoxide (CO) in metropolitan areas. Furthermore, it contributes approximately 5% of the global CO2, the famous greenhouse gas (Damtoft et al., 2008, Abu-Allaban and Abu-Qudais, 2011, Rai and Mishra, 2015). Therefore, there is an increasing need for tools that would allow for proper and objective quantification of the performance of industries with respect to the environment (Tyteca, 1996).

Energy audits are the immediate method to improve energy efficiency, reduce energy consumption, and decrease atmospheric emissions (Su et al., 2013). Enhancing the energy efficiency of cement plants will remarkably contributes to improve energy consumption and CO2 emissions and therefore, they can benefit from the quality monitoring tools having already been used for decades. One powerful method for monitoring the production processes, reducing variability, and achieving stability is statistical process control (SPC) (Montgomery, 2009). SPC is one of the most highly used quality control techniques in the industry and is perceived as a continuous and long-term benefits technique. The first productivity control application used in industrial manufacturing developed in the 1920s by Shewhart (Shewhart 1931). Edward (1982) incorporated this strategy as one of the pillars of the so-called total quality management which now has numerous applications in industrial processes, education, and services.

A given process can only be improved if there are some tools available for timely detection of an abnormality due to assignable causes. This timely and online signal of an abnormality (or an outlier) in the process could be achieved by plotting the process data points on an appropriate statistical control chart. These control charts can only tell that there is a problem in the process, but cannot tell anything about its cause. Investigation and identification of the assignable causes associated with the abnormal signal allow timely corrective action. As a result the variability in the process reduces and the process gradually takes to the next level of the improvement. This is an iterative process resulting from continuous improvement until abnormalities are no longer observed in the process. Whatever variation is observed is only due to common causes (Mukundam et al., 2013).

Moreover, SPC can be used to assess the inherent variability of energy consumption monitoring systems and indicates when to interfere in order to return a process back to within control parameters. It can also determine whether process is capable with respect to established standards or requirements. In recent years, several groups have published papers which illustrate how SPC can be applied to the different industrial processes such as cement production process.

Afkhami et al. (2015) used the Cumulative SUM of differences (CUSUM) statistical method to identify changes in historical energy performance patterns and monitor the energy saving actions implementation period. Castañón et al. (2015) conducted a statistical study with the aim of optimizing the production process at a Spanish cement factory relating kiln parameters to clinker quality.

Here, this research paper reports the findings using SPC for clinker energy consumption monitoring in an Iranian cement production plant. First, this paper studied its performance in the quality control procedure by monitoring the clinker energy consumption. This research presents a long-term record of the measurements, and then establishes the trial control limit of the existing process so that it could start phase I of the process improvement by using these control limits for monitoring of process. Then this paper evaluates process performance to represent the ability of the process to meet the energy performance along with the execution of national standard, ISIRI 7873, when the process comes under statistical control.

This paper is structured as follows: Materials and methods are introduced in section 2, and calculating required elements for generating the I-Chart are then described in details. In section 3, monitoring and data analysis of the thermal energy consumption is reported and normality test of the data and process performance indices are then considered. Finally, conclusion and some directions for future research are given in Section 4.

2. Materials and Methods

Materials and methods need to be designed and validated in order to get the expected desired results (Tirkolaee et al., 2017; Hosseinabadi and Tirkolaee, 2018). There are various control charts that are available for monitoring purposes. Selection of a control chart for a given process depends on two things, first is the phase of the process improvement and second consists of the type of data available and the rational sub grouping (Montgomery 2007). There are two phases in statistical process control. Phase (I) begins to acquire data and calculate trial control limits to identify deviations that can highlight specific causes which must be fixed. Then any out-of-control points with an assignable cause are discarded and the trial is resumed (Lopez-Tarjuelo, Luquero-Llopis et al. 2015). Occasionally, unexplained out-of-control observations are found in phase (I) and usually the process is not under statistical control. The main objective is to monitor forthcoming batches for any outliers and assignable causes associated with it, followed by investigation and process improvement through incorporating good deviations and eliminating bad ones from the process. Once all assignable causes are removed from the process, this research paper takes these defined limits as the monitoring values for phase (II) in which it controls the potential shifts in the variation of the system.

The other criteria for the selection of an appropriate control chart are the type of data available and rational sub grouping (Montgomery, 2007). An I-MR chart plots individual data (I chart) and moving ranges (MR chart) over time which is the measure of variability of the given data. This paper uses this chart to monitor process center and variation when it is difficult or impossible to group measurements into subgroups. This occurs when production volume is low or products have a long cycle time and also when the measurements are expensive.

When data are collected as individual observations, this research cannot calculate the standard deviation for each subgroup. So, the moving range is an alternative method to calculate process variation by computing the ranges of two or more consecutive observations.

I-MR chart is also the most appropriate chart to be used in phase (I) of the improvement for individual observations. It is a powerful tool for detecting large shifts in the process (more than $\pm 1.5\sigma$).

In the present case, the I-MR chart is the most appropriate chart to be used in phase (I) of the improvement for individual observations where only one data from manufacturing process was provided at a given time and data are not collected in subgroups,.

When a process enters phase (II), it is characterized by a stable process with inherent variations (due to common causes) in the process. Now, the main focus is on monitoring and detecting the small changes (less than$\pm 1.5\sigma$) in the process. Therefore, more sensitive control charts such as CUSUM and EWMA charts are employed (Mukundam et al., 2013).

2.1. I-Chart Generation

2.1.1. Moving Range (MR)

MR is the absolute value of the difference between two consecutive observations as shown by Eq. (1). MR values are used as a measure of the variability of the data points.

$$MR_i = |x_i - x_{i-1}| \tag{1}$$

2.1.2. Moving Range (MR)

The average of all range values is calculated by eq. 2. This value is on the basis of calculating the standard deviation of the process.

$$\overline{MR} = \frac{1}{N-1}\sum_{i=2}^{N} MR_i \tag{2}$$

2.1.3. Standard Deviation ($\boldsymbol{\sigma_{MR}}$)

The standard deviation of the process is calculated from the average moving range as shown by Eq. (3). It represents the average variation of the process. The main aim of the control charts is minimize this variation.

$$\sigma_{MR} = \frac{MR}{d_2} \tag{3}$$

Where d_2 is a control chart constant and it depends on the number of samples used for calculating MR, and in the case of two observations, as in this work, d_2 =1.128.

2.1.4. Mean Assay ($\bar{X}$)

The Average value of the assay of all the batches is calculated by Eq. (4). This becomes the center line of the I-Chart.

$$\bar{X} = \frac{1}{N}\sum_{i=1}^{n} x_i \tag{4}$$

2.1.5. Control Limit for I-Chart

The I-Chart is constructed through assuming that it is very unlikely that a new observation exceeds the distance $3\sigma_{MR}$ from the average value of the previous sample. So, both UCL and LCL are calculated on the basis of the mean and σ_{MR} values obtained from individual data set. Control limits are calculated in such a way that they are $\pm 3\sigma_{MR}$ away from the process mean $\bar{X}$, as shown by Eqs. (5) and (6). This is the natural control limit of a process.

$$UCL = \bar{x} + 3\sigma_{MR} \tag{5}$$

$$LCL = \bar{x} - 3\sigma_{MR} \tag{6}$$

The I-chart is then prepared by plotting the mean, UCL, LCL, and individual values of the assay.

2.2. MR-Chart for the Assay

MR chart has its own control limits and center line. Control Limits for MR-Chart are calculated by Eqs. (7) and (8).

$$LCL_{MR} = D_3\overline{MR} \tag{7}$$

$$UCL_{MR} = D_4\overline{MR} \tag{8}$$

Here, D_3 and D_4 are the control chart constants and depend on the number of samples used for the calculation. In the case of two observations D_3 and D_4 are calculated as 0 and 3.268 respectively.

3. Monitoring and Data Analysis of the Thermal Energy Consumption

Herein, this paper presents the endeavor to deploy statistical control charts for the first time (i.e., phase I of the process improvement) to the manufacturing process of cement production in an Iranian cement plant. This study is only limited to the process system boundary which includes clinker production. This system consumes more than 90% of the total energy consumption in cement production plant. So, within the process system boundary, this research paper retrieved the quality control records from 1/01/2013 to 1/01/2016 focusing the monthly average index of thermal energy consumption shown in table 1 respectively, that place the studied plant in the group of high energy consumption in comparison with the targeted values of 770 (kcal/kg clinker) given in the ISIRI 7873 standard.

Table 1. Energy Consumption Data for Clinker Production Process in the Studied Cement Plant.

Row	Month	Thermal Energy Consumption (kcal/kg Clinker)
1	February 2013	842
2	March 2013	810
3	April 2013	790
4	May 2013	782
5	June 2013	839
6	July 2013	
7	August 2013	798
8	September 2013	823
9	October 2013	818
10	November 2015	786
11	December 2013	840
12	January 2013	899
13	February 2014	863
14	March 2014	775
15	April 2014	783
16	May 2014	800
17	June 2014	828
18	July 2014	803
19	August 2014	804
20	September 2014	822
21	October 2014	841
22	November 2014	802
23	December 2014	827
24	January 2014	792
25	February 2015	867
26	March 2015	838
27	April 2015	810
28	May 2015	829
29	June 2015	828
30	July 2015	860
31	August 2015	839
32	September 2015	848
33	October 2015	812
34	November 2015	807
35	December 2015	813
36	January 2015	820

3.1. Normality Test of the Data

I-MR charts are so sensitive to the normality of the data. Normality test is performed subjecting the data set from Table 1 to the Anderson−Darling test using Minitab as shown in Figure 1. Given a 'p value' of 0.673, indicating that $p > 0.05$, this results are in acceptance of a null hypothesis and this meaning that the data set was normally distributed and could be used for I-MR chart.

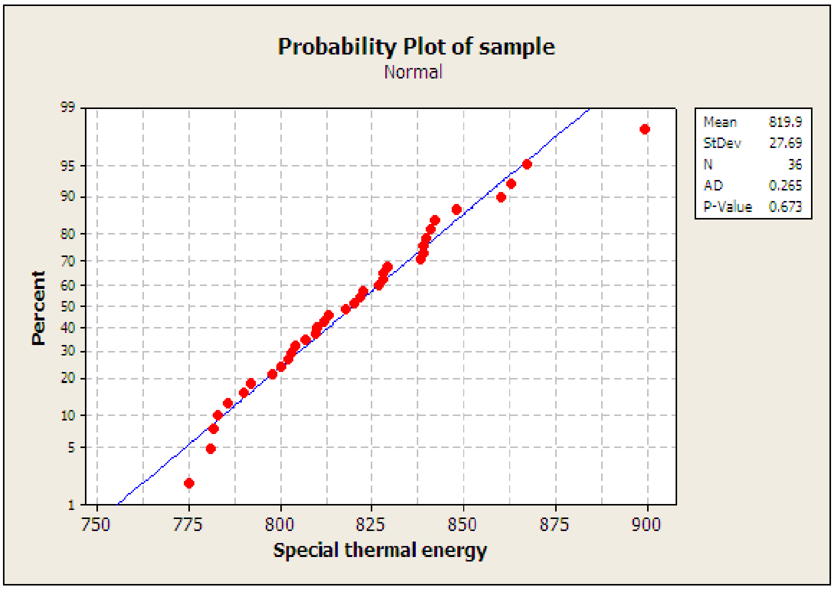

Fig. 1. Probability Plot of Samples for Normalization of Data**.**

Given the run-chart as shown in Figure 2, there is not a certain trend in the data and it can be concluded the data are independent.

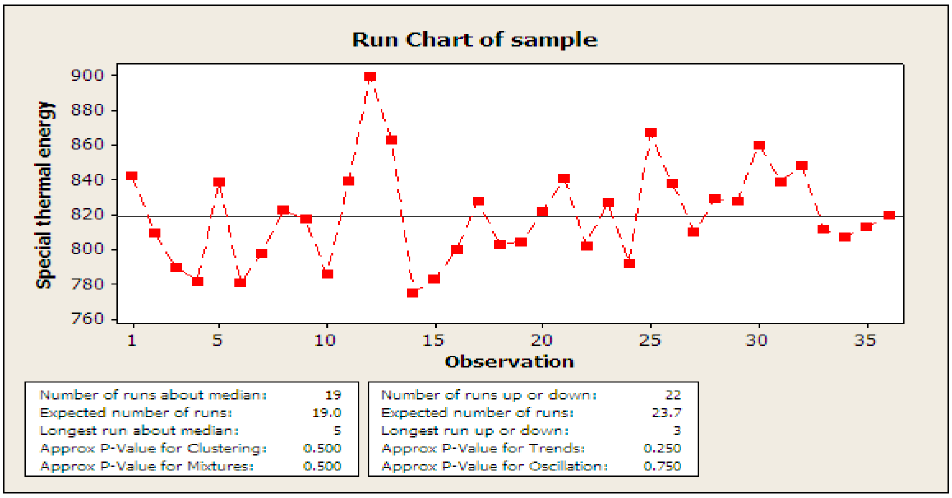

Fig. 2. Run Chart of Samples.

As a first step, the I-MR chart was prepared deliberately including all data points from Table 1 as shown in Figure 3.

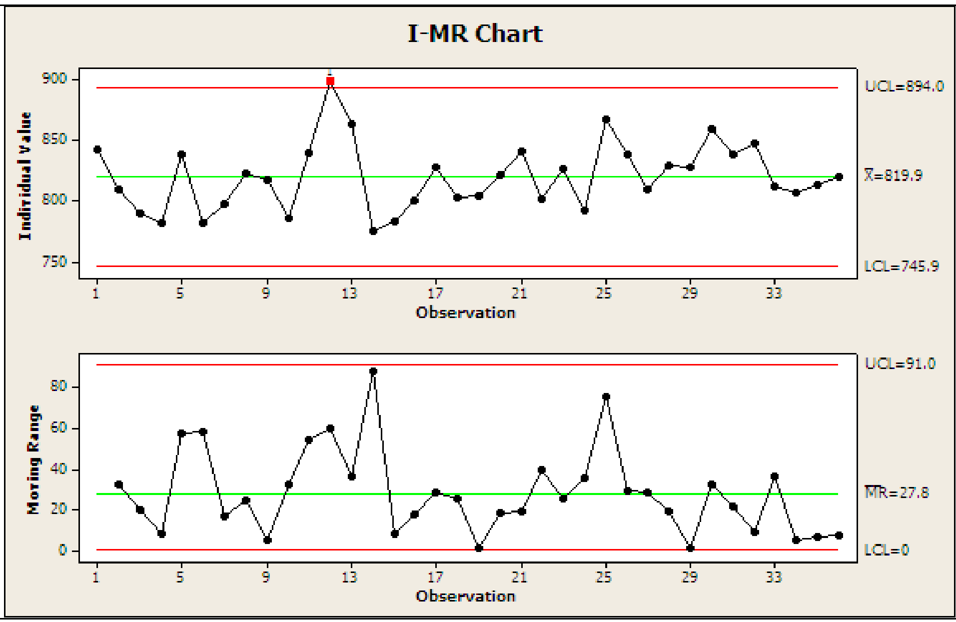

Fig. 3. Primarily I-MR Chart.

It is evident that the 12th data point lie outside the UCL, indicating that the process has gone out of control, which in turn indicates a possible assignable cause associated with this shift. This required investigation and corrective action in the process.

When control charts are prepared for the first time to estimate the natural control limit of the process, it will be carried out on the basis of the historical data. Hence, it is generally assumed that assignable causes for the outliers were identified and the process was rectified at that point intime. On the basis of this assumption, control limits were recalculated by ignoring out-of-control points (in the present case, 12th). Hence, new data set obtained after ignoring outliers could be used for I-MR chart as shown in Figure 4.

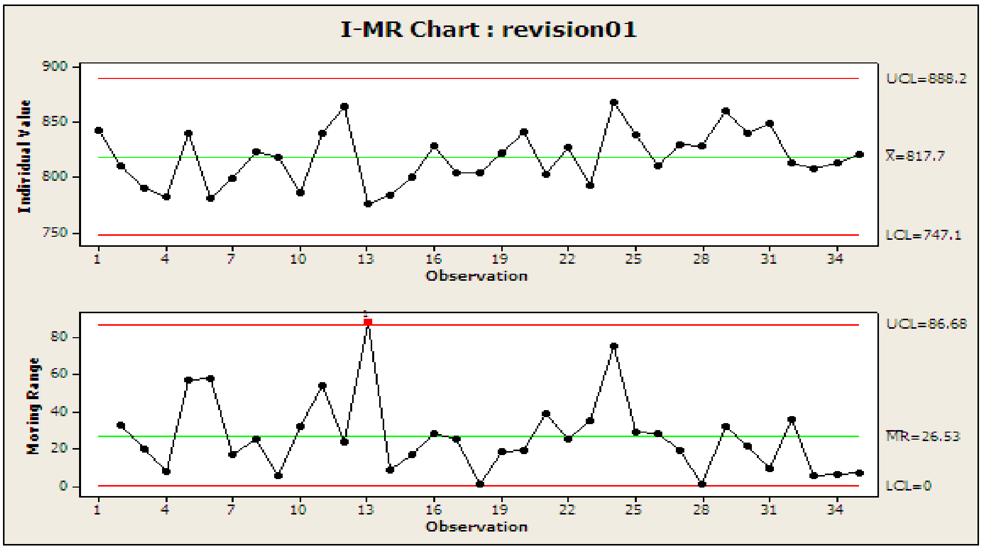

Fig. 4. I-MR Chart after Eliminating Outlier.

Similarly, the assay of the 13th was out of LCL indicating a possible assignable cause associated with this shift and required investigation and corrective action in the process.

After recalculation of trial control limits for Assay (ignoring 13th), and applying new data set, the final I-MR chart is obtained. The reasons for new assignable causes would then be identified and rectified till there are no more assignable causes and the process is said to be under statistical control as shown in Figure 5.

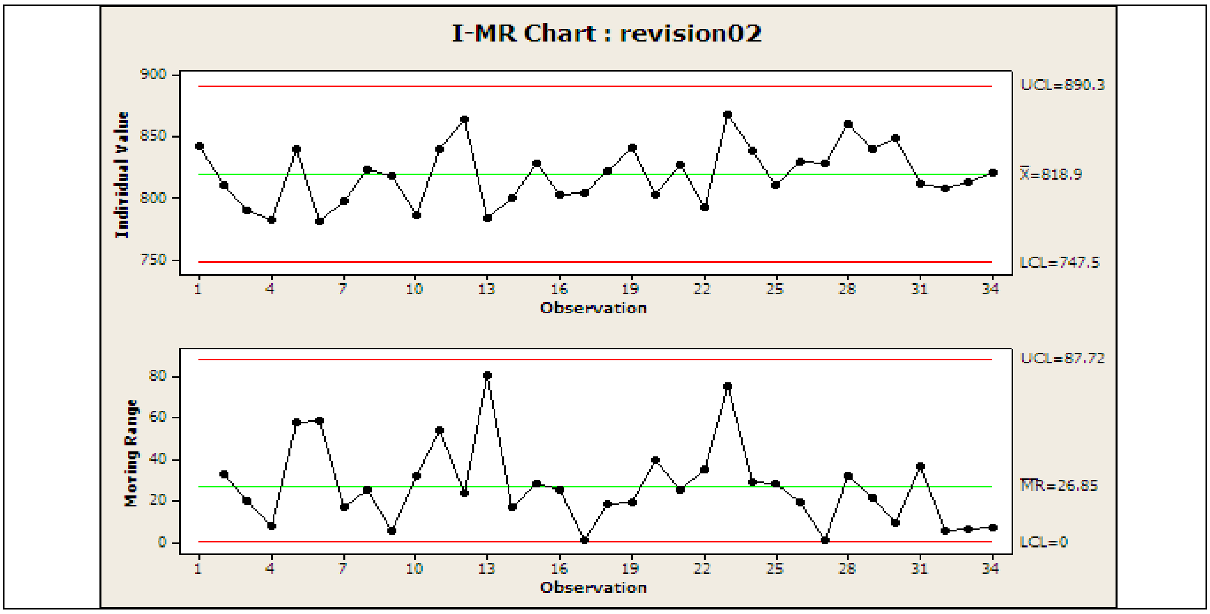

Fig. 5. The final I-MR Chart.

This marks the termination of phase (I) of the process control. The main purpose of the present exercise was to obtain trial control limits for the existing process, so that this paper could start phase (I) of the process improvement through using these control limits for monitoring of the process.

3.2. Process Performance Indices

Performance index is a dimensionless number used to represent the ability of the process to meet the customer's specification for a given quality attribute. Process performance indices are calculated out of curiosity to assess the overall 'σ level' of the process for the assay. This will make more sense when the process comes under statistical control (Montgomery 2007).

The process capability ratio (Cp and Cpk) is used to express process capability and to determine how much of the process variation is accommodated within its specification band. It is limited by the high technical specification (USL) and low technical specification (LSL) as follow:

$$C_p = \frac{usl - lsl}{6\sigma} \tag{9}$$

$$C_{Pu} = \frac{usl - \mu}{3\sigma} \tag{10}$$

$$C_{Pk} = min\{cpu\,, cpl\} \tag{11}$$

$$C_{Pm} = \frac{usl - lsl}{6\sqrt{\sigma^2 + (\mu - T)^2}} \tag{12}$$

The targeted values of 770 (kcal/kg clinker) for thermal energy consumption based on ISIRI 7873, is considered as a high technical specification to calculate process capability ratio (C_P and C_{Pk}).The guidelines give a value of 1.25 for these indices in an under control process.

As can be seen in Figure 6, C_{Pu} and C_{Pk} give a value of -0.69. This means that the process mean is beyond the scope of the technical control limits. Also, this indicates inefficiency of the process with respect to the control limits, so the process needs to be reviewed and consequently the establishment of proper saving actions is necessary to facilitate energy performance along with the execution of ISIRI 7873.

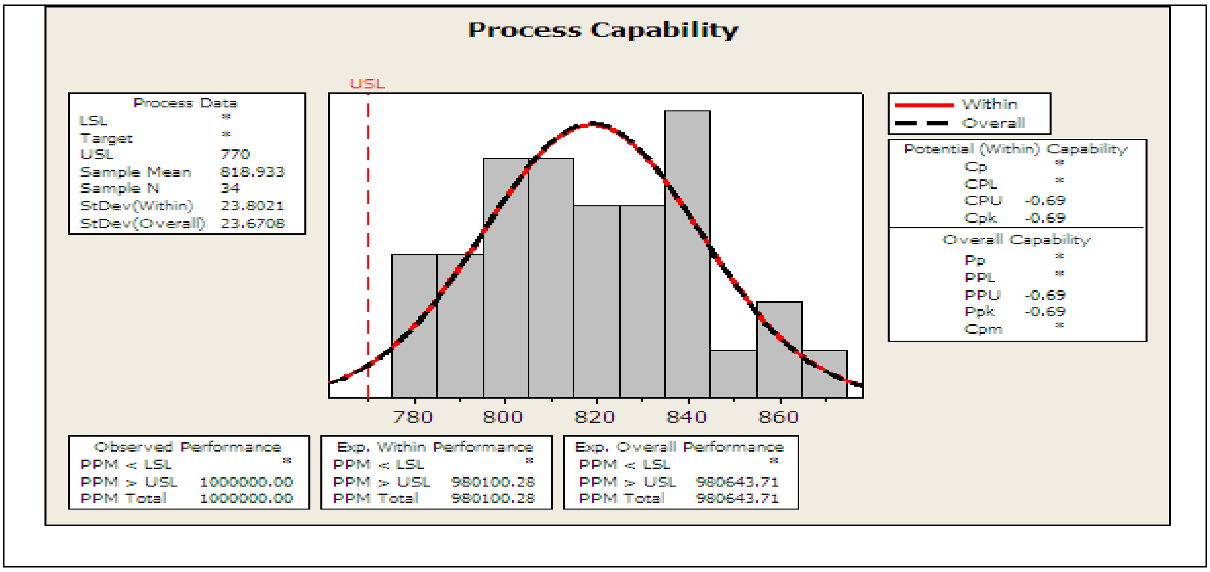

Fig. 6. Process Capability Indices.

4. Conclusion

SPC can be used to assess the inherent variability of energy consumption monitoring in cement factory. It can also indicate whether the process is capable of meeting the expected energy performance. Here, to assess the energy consumption monitoring, SPC is deployed on clinker production process and a long-term record of the measurements of clinker energy consumption are retrieved. All data of phase (I) were under statistical control. The process performance was also evaluated by calculating the process capability ratio to represent the ability of the process to meet the energy performance along with the execution of national standard, ISIRI 7873. The process is inefficient because the process mean is beyond the scope of the technical control limits. So, the process needs to be reviewed and the establishment of proper saving actions is necessary to improve energy efficiency, to reduce energy consumption, and consequently to decrease atmospheric emissions. Investigation and identification of the assignable causes associated with the abnormal signal and the use of more sensitive control charts such as CUSUM and EWMA in phase (II) of the process improvement are interesting subject for future research.

References

Abu-Allaban, M., & Abu-Qudais, H. (2011). Impact assessment of ambient air quality by cement industry: A case study in Jordan. *Aerosol and Air Quality Resarch*, 11(7), 802-810.

Afkhami, B., Akbarian, B., Beheshti, N., Kakaee, A. H., & Shabani, B. (2015). Energy consumption assessment in a cement production plant. *Sustainable Energy Technologies and Assessments*, 10, 84-89.

Castañón, A. M., García-Granda, S., Guerrero, A., Lorenzo, M. P., & Angulo, S. (2015). Energy and environmental savings via optimisation of the production process at a Spanish cement factory. *Journal of Cleaner Production*, 98, 47-52.

Damtoft, J. S., Lukasik, J., Herfort, D., Sorrentino, D., & Gartner, E. M. (2008). Sustainable development and climate change initiatives. *Cement and concrete research*, 38(2), 115-127.
Edward, D. W. (1982). Out of the Crisis: Quality, Productivity, and Competitive Position. *Cambridge (Mass.) Mass. Inst. of Technology*. Center for Advanced Engineering Study: Cambridge University Press.

Hosseinabadi, A. A. R., & Tirkolaee, E. B. (2018). A Gravitational Emulation Local Search Algorithm for Task Scheduling in Multi-Agent System. *IJOAS*, 1(12), 11-24.

Liu, G., Yang, Z., Chen, B., Zhang, J., Liu, X., Zhang, Y., and Ulgiati, S. (2015). Scenarios for sewage sludge reduction and reuse in clinker production towards regional eco-industrial development: a comparative emergy-based assessment. *Journal of Cleaner Production*, 103, 371-383.

López-Tarjuelo, J., Luquero-Llopis, N., García-Mollá, R., Quirós-Higueras, J. D., Bouché-Babiloni, A., Juan-Senabre, X. J., and Santos-Serra, A. (2015). Statistical process control for electron beam monitoring. *Physica Medica*, 31(5), 493-500.

Montgomery, D. C. (2009). Quality improvement in the modern business environment. *Introduction to Statistical Quality Control*, 3-47.

Montgomery, D. C. (2007). Introduction to statistical quality control, *John Wiley & Sons*.

Mukundam, K., Varma, D. R., Deshpande, G. R., Dahanukar, V., & Roy, A. K. (2013). I-MR control chart: A tool for judging the health of the current manufacturing process of an API and for setting the trial control limits in phase I of the process improvement. *Organic Process Research & Development*, 17(8), 1002-1009.

Nguyen, Q. A., & Hens, L. (2015). Environmental performance of the cement industry in Vietnam: the influence of ISO 14001 certification. *Journal of Cleaner Production*, 96, 362-378.

Rai, P., & Mishra, R. M. (2015). Study of Seasonal concentration of SPM, RSPM, SO 2 and NO x in the ambient air near JP cement plant, Rewa (MP). *International Journal of Pharmacy & Life Sciences*, 6(2).

Shewhart, W. A. (1931). Economic control of quality of manufactured product. *ASQ Quality Press*.

Su, T. L., Chan, D. Y. L., Hung, C. Y., & Hong, G. B. (2013). The status of energy conservation in Taiwan's cement industry. *Energy policy*, 60, 481-486.

Tirkolaee, E. B., Goli, A., Bakhsi, M., & Mahdavi, I. (2017). A robust multi-trip vehicle routing problem of perishable products with intermediate depots and time windows. *Numerical Algebra, Control & Optimization*, 7(4), 417-433.

Tyteca, D. (1996). On the measurement of the environmental performance of firms—a literature review and a productive efficiency perspective. *Journal of Environmental Management*, 46(3), 281-308.

Von Bahr, B., Hanssen, O. J., Vold, M., Pott, G., Stoltenberg-Hansson, E., & Steen, B. (2003). Experiences of environmental performance evaluation in the cement industry. Data quality of environmental performance indicators as a limiting factor for benchmarking and rating. *Journal of Cleaner Production*, 11(7), 713-725.