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X-bar Chart Based on Six Sigma to Continual Quality Improvement: Implementation on Oil Vapor Pressure Characteristic, at Yemen's Aden oil refinery(*)

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مخطط X-bar استناد على مفهوم ستة سيجما لتحسين الجودة المستمر: بالتطبيق على خصائص ضغط بخار البترول في مصفاة عدن للبترول باليمنية

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الملخص باللغة العربية

لطالما كان إنتاج منتجات عالية الجودة مع إبقائها في متناول الجميع تحديًا في الاسواق التنافسية الحالية. نتيجة لذلك، يبحث المنتجون بنشاط عن طرق لخفض التكاليف وزيادة الكفاءة. مخطط التحكم هو الأداة الأكثر استخدامًا في الممارسات العملية للحفاظ على التحكم في العملية بتكلفة منخفضة. مخطط X-bar هو مخطط التحكم الأكثر استخدامًا نظرًا لبساطته. على الرغم من حقيقة أن متوسط العينة هو مقدر غير متحيز لمتوسط المجتمع، إلا أن العيب الرئيسي في مخطط X-bar هو أن الانحراف المعياري للمجموعة غير معروف. مع الاشارة الى أن هناك العديد من الطرق لتقدير الانحراف المعياري، وبالتالي فان تعدد طروق لتقدير للانحراف المعياري يمكن أن تؤدي إلى استنتاجات مختلفة. في هذه الدراسة، تم تنفيذ نهج احصائي مقترح لتقدير الانحراف المعياري لمجتمع الدراسة استناد الى مفهوم ستة سيجما (Six Sigma) ومفهوم مقدرة العملية الاحصائية لغرض تقليل التباين في خاصية ضغط بخار البترول Oil Vapor (Pressure) في عملية تكرير مصافي عدن للبترول باليمن. من خلال عينة بحجم 25 تم جمعها بشكل عشوائي، كل عينة تحتوي على أربعة عناصر. وبعد اجراء الاختبارات الاحصائية الاساسية للبيانات مثل: اختبار التوزيع الطبيعي للبيانات (Normality Test, unit root, Autoregressive Test and Capability) تم اجراء التحليل الاحصائي الاولي ووفق نتائج مؤشرات مقدرة العملية فان نتائج الدراسة الحالية تشير، بإن مستوى السيجما التي تعمل علية مصفاة عدن للبترول أقل من 4 سيجما، وبالتالي هناك حاجة لتطبيق المنهج المقترح في هذه الدراسة والمتمثل في (مخطط X-bar استناداً إلى مفهوم ستة سيجما كونه منهج فعال في تقليل تباين العملية. علاوة على ذلك، فهو منهج قادر على الحفاظ على متوسط العملية بالقرب من هدف العملية (Target)، مما يؤدي إلى تحسن قدرة العملية، وبالتالي تزداد مستويات السيجما. نتيجة للزيادة في مستويات سيجما، يتحسن أداء عملية تكرير البترول بخصائص ضغط البخار. أخيرًا، تقدم هذه الورقة الأساسيات والمهارات اللازمة للباحثين والمهندسين في مراقبة الجودة لاستخدام Six Sigma لتقليل التباينات في العملية الصناعية.

الكلمات المفتاحية: ستة سيجما، التباين، التحكم الإحصائي في العمليات، مؤشرات مقدرة العملية، ضغط بخار البترول، حدود المواصفات العليا والسفلى.

X-bar Chart Based on Six Sigma to Continual Quality Improvement: Implementation on Oil Vapor Pressure Characteristic, at Yemen's Aden Oil Refinery

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Abstract

Producing higher-quality products while keeping them affordable has always been a challenge in today's competitive market. As a result, producers are actively searching for ways to cost-cutting and increase efficiency. A control chart is the most widely used SPC tool in practice for maintaining process control at a low cost. The X-bar chart is the most widely used control chart due to its simplicity. Despite the fact that the sample mean is an unbiased estimator of the population mean, but the main drawback of the X-bar chart is that the population standard deviation is unknown. With the knowledge available to researchers there are many methods of estimating the unknown standard deviation that can lead to different conclusions. In this study, a groundbreaking approach to estimate the population standard deviation from the perspective of Six Sigma quality that is implemented for the design of the suggested control-chart for mean is X-bar Chart based on the Six Sigma, from the standpoint of Six Sigma quality and the process specification. This paper presents Six-Sigma SS evaluation focusing on the process capability with SS-X_{-bar} control chart was used to minimize variations in the oil Vapor Pressure characteristic in an oil refining process in Aden, Yemen, a twenty-five oil Vapor Pressure characteristic samples with a normal distribution were collected at random, each sample containing four items. After having the main statistical tests like the Normality Test, unit root, Autoregressive Test and Capability, it has been found that the sigma level used in the Aden refinery is less than 4. According to the findings of this analysis, the X chart based on the six-sigma estimation method is effective in reducing variance in the oil Vapor Pressure characteristic. Furthermore, it is able to keep the process mean near to the target, leading towards improving the process. As the process capacity improves, the sigma levels increase. As a result of the increase in sigma levels, the process refinery of oil Vapor Pressure characteristic performance improves. Finally, this paper presents the fundamentals and skills needed for quality control researchers and engineers to use Six Sigma to minimize variances in the industrial process.

Keywords: Six Sigma, Variance, Statistical Process Control, Process Capability Petroleum Vapor Pressure. Upper and Lower Quality Limits.

1. Introduction

Batch processing is used in industries sectors such as polymers, pharmaceuticals, food and beverage, semiconductors, and biochemicals. (E.g. see Blomer & Gunther, 2000; c, Castagliola, Fichera, & Nenes, 2013; Das & JAIN, 1997; De Beer et al., 2011) The importance of monitoring batch-to-batch variance and identifying irregular events in the early stages of development c be overstated. The control chart, specifically the X control chart, was first introduced by Shewhart (1931) to differentiate normal expected causes of process variability from special or assignable causes, and is still widely used today to measure the variability of a given process.

The values of three parameters must be determined by using an X control chart: sample size (n), control limits U-L=K, and sampling interval length (h).

Economic designs seek to reduce costs or increase profits per unit of time or per unit made, without constraints. When a single assignable trigger occurs, Duncan, (1956) proposed the first economic model for evaluating the three design parameters for the control chart that minimizes the total cost. Following that, a lot of work was done to refine the design of the control chart based on economic criteria. Lorenzen & Vance, (1986) suggested a single model that could be generalized to most forms of control charts that work or shut down when searching for and laminating assignable triggers.

The use of an economic approach to optimize X-bar chart parameters has been extensively discussed in the literature (Avinadav, Perlman, & Cheng, 2016; Ho & Case, 1994; Montgomery, 1980; Ng, Khoo, Chong, & Lee, 2019; Svoboda, 1991; Wang, Fu, Yuan, & Dong, 2018) Centered on an expansion of Lorenzen & Vance, (1986) total cost model, Ershadi, Noorossana, & Niaki, (2016) proposed an econ omic design model with variable sample size. However, Woodall, (1986) noted that an economically built control chart produces a large number of false alarms. As a consequence, when designing the control map, the goal should be to minimize the cost function while adhering to certain statistical constraints. This is known as the eco-nomic-statistical control chart style, and it was first suggested by Saniga, (1989) to combine economic and statistical objectives. However, it is more expensive than a simple economic design. Celano et al.,(2013) has written a comprehensive analysis of the literature on this style of design. Researchers such as (Chih, Yeh, & Li, 2011; Lee, Khoo, Chew, & Then, 2020; Niaki & Ershadi, 2012; Wan & Zhu, 2021; Wang et al., 2018; Yu, Tsou, Huang, & Wu, 2010) have used various optimization methods for this design. Quality and cost have become crucial variables that manufacturers must recognize in conventional *X* Production (Lee et al., 2020). Companies are currently facing major challenges in staying competitive and delivering high-quality goods while maximizing profit and lowering operating costs.

The majority of industries and manufacturing firms strive to enhance their products' quality and efficiency. This rivalry has prompted businesses to use statistical quality management techniques and strategies in order to increase product efficiency (Allam, Becker, Baudouin, Bigot, & Krumpipe, 2014). Statistical methods have been used to measure and improve product quality since the invention of the ordinary least squares system. Carl Friedrich Gauss (1777–1855), for example, introduced the natural curve principle as a norm for measuring variations.

In 1924, A. Shewhart introduced statistical process control (SPC) and other important statistical tools, such as X-bar and R-bar charts; this study represented the SPC system stream. Pareto's work, on the other hand, represented the root cause analysis stream(Allen, 2006). The emergence of process capability indices (PCIs) was discussed by Deming, Ishikawa, and Juran in 1974. In industries, process management has become a critical tool for improving the quality of a product or service. The Six Sigma principle has been applied by a variety of well-known global companies to boost product quality. Bill Smith created Six Sigma initiatives in early 1986 to evaluate Motorola's capability process. Smith attributed the error to improvements in the company's internal process, emphasizing the potential of improving system efficiency by reducing errors (Allen 2006).

To minimize variations in a phase, Six Sigma employs statistical tools and methods such as SPC and DOEs (Allen 2006). The word "Six Sigma" comes from the statistical field of PCIs, which are tools for evaluating a process's efficiency in producing significant outputs within defined limits. When the index is high, the number of items that fall outside of the requirements limits is low. The method yield index is used to determine performance parameters in particular.

PCIs are statistical quantifications with no units that can be used to compare the actual output of a process to its tolerance limit, which is calculated based on user requirements. Furthermore, process capability offers numerical metrics to determine a manufacturing process' suitability for producing goods that meet excellent design limits (Parchami, Sadeghpour, Nourbakhsh, & Mashinchi, 2014; Pearn, Shiau, Tai, & Li, 2011). PCIs and Six Sigma efficiency work together to create long-term defects that are less than 3.4 per million opportunities (DPMO). In terms of numbers, if a process produces less than 3.4 DPMO, the error rate is 0.0003 percent.

A Six Sigma process with a 3.4 DPMO is the most widely accepted definition. This definition assumes that a process following the normal distribution would have 3.4 parts per million above a 4.5-standard-deviation point. A Six Sigma method with a 3.4 DPMO has a sig-ma of 4.5, which is the product of 6 minus the 1.5 change of long-term variations (Gupta, 2015). Standard deviation and process variability, such as defect per unit of variability, are denoted by the Greek letter σ Abdul, Ali, & A.R, 2021). Statistically, a Six Sig-ma level can reduce internal process variations.

The ability to predict the capability of efficient processes can be supported by the functionality of minimizing variation. In other words, as six sigma efficiency increases, the degree of variance decreases. In this case, Six Sigma is described as a statistical technique for assisting companies in their ability to re-examine variations in their processes ((Zimbro, Power, Miller, Wilson, & Johnson, 2009).

Six Sigma is defined as a deviation indicated by 6σ; σ is the terminological definition of SPC techniques in controlling quality operations included in the broader topic of sigma quality control. It requires the execution of efficient processes with minimal errors, and it can be defined as a deviation indicated by 6σ; σ is the terminological definition of SPC techniques in controlling quality operations included in the broader topic of sigma quality control. This symbol represents the rate of any operation's variance. Six Sigma is a statistical measure that indicates the standard deviation of a set of data from six standard deviations or dimensions. It denotes the reduction of variance (i.e., errors) to six standard deviations in the effective process. Six Sigma measurements are commonly used to assess the sigma quality levels' results. Sigma is a parameter for estimating process efficiency that denotes the presence of uncertainty in a process and can be used as a measure of statistical process technology (F. Ali & Ahmed, 2016). Efficiency (based on sigma quality levels) and expense (divided into two groups, world-class organization and non-competitive organization) are used to categorize industrial organizations (Zimbro et al., 2009).

2. EVALUATION AND MEASUREMENT OF SIX SIGMA

Measurement is an essential goal for implementing Six Sigma. Six Sigma can be successfully implemented using statistical tools and methods and focusing on the following themes:

2.1 Defining variations

Understanding and defining variations are vital criteria used to raise the quality of processes or a product. Variation, which is inherent in all process at certain levels, causes defects. If the variation is low, then the process or the product is regarded as defect free. As such, variation quantification is an essential and critical step toward the improvement of a product or service. Variations should also be clarified and described in order to improve the quality of products or system. Toward the end of this development, a detailed understanding of the causes and types of variations should be completed in order to assess the best course of action for minimizing variations and, as a result, enhancing the product or service's consistency (Muralidharan, 2015).

2.1.1 Estimation of Sigma

Standard deviation (SD) estimation is important and serves as the base for statistical analysis of process capacity. Capability indices derived from survey statistics are subject to statistical uncertainty, which has an effect on the indices calculated. The estimated PCIs differ from the actual PCIs. These problems have prompted (encouraged) several researchers to highlight the importance of sigma estimation in Six Sigma studies (Bissell 1990; Chakraborti et al. 2008; Chakraborty and Chatterjee 2016; Chen et al. 2003; Franklin and Wasserman 1992; Hsu et al. 2008; Lin et al. 2005; Pearn et al. 1992; Wen Lea Pearn 2014).

In these studies, improvement in processes is examined and estimated in terms of sigma levels. This paper provides a method for estimating the Vapor Pressure characteristic of oil products in Yemen. Standard deviation should be estimated to identify variability in the oil refinery process. This paper also presents theoretical fundamentals and general literature on the concept of Six Sigma, PCIs, and different methods for estimating standard deviation on PCIs Data were collected for a specific oil characteristic, namely, Vapor Pressure. The analysis is performed to determine standard deviation and variability and evaluate whether the refinery process of Vapor Pressure characteristics produces oil that meets the specifications limits. From an organizational context, Parts per Million (PPM) defect rate or Defect per million Opportunities (DPMO) rate is first calculated and then converted into a Six Sigma measurement unit, which considers the rate as the 1.5σ shift. Several models can be used to estimate the standard deviation. These models can be categorized as follows:

I. Standard deviation estimators that are widely used

The first estimator of sigma for the standard deviation is the unbiased estimator, which is defined as follows:

$$\hat{\sigma}_{LT} = \sqrt{\frac{\sum_{i}^{n}\sum_{j}^{m}(X_{ij} - \overline{\overline{X}})^2}{(mn-1)}} \qquad (1)$$

Where $(mn-1)$ represents size and subgroups; $i\ x_{ij}\ i = 1,\ldots n,\ \ j = 1,\ldots m$ represent the processed data collected; $\overline{\overline{x}}$ grand mean used to estimate μ.

II. Models based the control charts:

The following mathematical expressions can be used to calculate standard deviation using control charts.

$$\hat{\sigma}_R = \frac{\overline{R}}{d_2 \times (n)} \qquad (2)$$

where $\overline{R} = \frac{\sum_{i=1}^{m} \overline{R}}{N}$ is the mean of the sample ranges, calculated as follows: $R = \max(x) - \min(x)$;is the sample size used to formulate control chart d_2 constant values and $\hat{\sigma}_R$ used to estimate (standard deviation).

$$\hat{\sigma}_S = \frac{\overline{S}}{C_4(n)} \qquad (3)$$

Where are $\overline{S} = \frac{\sum_{i=1}^{m} \overline{S}}{N}$, C_4 and $S_i = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} \left(x_{ij} - \overline{x}_i\right)^2}$ Constant values for the is used for estimate $\hat{\sigma}_S$ control chart dependent on samplesize and C_4 (standard deviation) , Many SQC references are commonly available (Montgomery 2009).

$$\hat{\sigma}_{S_i} = \frac{Si}{C_4(V)} \qquad (4)$$

$\hat{\sigma}_{S_i}$ Is used to estimate pooled sigma. In this case,

$V = \left(\sum_{i=1}^{m} n\right) - m + 1$, and $S_i = \sqrt{\frac{1}{n-1} \sum_{j=1}^{n} \left(x_{ij} - \overline{x}_i\right)^2}$ are unbiased (Luko 1996).

$$\hat{\sigma}_{w_i} = \frac{1}{\sum_{i=1}^{N} w_i} \cdot \sum_{i=1}^{N} \frac{w_i R_i}{d_2(n)} \qquad (5)$$

Where $\hat{\sigma}_{w_i}$ a minimal variance linear unbiased estimator is (MVLUE). This estimator is based on the weighted average of (N) unbiasedestimates in σ

the form $R/d_{2(n)}$ and $w_i = \frac{\left[d_{2(n_i)}\right]^2}{1-\left[d_{2(n_i)}\right]^2}$, it's built for circumstances with a widevariety of pooled sample sizes.

$$\hat{\sigma}_{hi} = \frac{1}{\sum_{i=1}^{N} h_i} \sum_{i=1}^{N} \frac{h_i s_i}{C_4(n)} \qquad (6)$$

The MVLUE approach is based on the subgroup norm $\hat{\sigma}_{hi}$, which is a weighted average of N unbiased estimates of σ of the form s_i/C_4 where $h_i = \frac{\left[C_{4(n_i)}\right]^2}{1-\left[C_{4(n_i)}\right]^2}$.

3. Relationship between 6σ levels and PCIs

The standard deviation is a calculation of the range of variations in any phase (S.D.). The standard deviation (S.D.) is a statistical parameter that determines range a value shift from the mean. Variations in the mean suggest an increase in error, which leads to more errors and lower process efficiency. Six Sigma is critical for reducing errors and error ranges while also improving product quality. Six Sigma is a statistical metric used to ensure that a production process meets a predetermined design limit (Gupta 2015; Şenvar and Tozan 2010).

PCIs are indicators or metrics that are used to assess a process' ability to generate units within defined limits (Montgomery 2009).The PCI concept offers numerical measures that can be used in industries to establish suitability in manufacturing (Pearn et al., 2014). Thus, companies can employ these measures to ensure that their products exhibit excellent quality and meet the pre-specified limits of the company (Parchami et al. 2014). Several researchers are interested in developing standards to measure the production process (Gupta, 2015). PCIs reflect the performance of the process and a summary of the occurrences in the numerical value of production. Process capability can be expressed as a function of the process variations (i.e., 6 σ) because the capability of the process is synonymous with its variation.

Statistically, PCIs are made up of a number of indices. C_p is one of the most common indicators C_p (Juran, 1974a). Statistically, C_p is determined by comparing the dependent curve to the Six Sigma normal distribution. Kane (1986) proposed the C_{pk} index to measure one side of the curve, while Chan et al. (1988) proposed theindex to measure process C_{pm} capability to cluster around the target.

All these indices can be employed in industries during manufacturing. The first index C_p is a capability index that signifies the width tolerance divided by the capability process, regardless of process centering. According Juran (1974), the C_p index is calculated as follows:

$$C_p = \frac{USL - LSL}{6\sigma} \qquad (7)$$

C_p This index was created to show the overall process performance by measuring the total magnitude of process variations in relation to the tolerance of manufacturing processes. C_{pk} Denotes a method with low variability and small proximity on mean. As a result, multiple indices may be used to integrate a target and measure the process' capability. (Muralidharan, 2015). These indices are presented as follows, according to Kane (1986):

$$\left.\begin{aligned} C_{pl} &= \frac{(\bar{\bar{X}} - LSL)}{3\sigma}, \\ C_{pu} &= \frac{(USL - \bar{\bar{X}})}{3\sigma}, \\ C_{pk} &= \min\left[C_{Pl}, C_{pu}\right] \end{aligned}\right\} \qquad (8)$$

Where LSL and USL The lower and upper specification limits, respectively, σ and $\bar{\bar{X}}$ are the process standard deviation and mean, respectively. Indices C_p, C_{pk} are used for processes with normal distribution and two-sided specification limits. Moreover, indices C_{pu} andd are C_{pi} intended precisely for processes with one-sided specification limits.

Table 1. PCIs and grading description.

Value of Capability	Grading	Sigma level
<1.	Inadequate	$1 \leq 3$
$1. \leq C_P < 1.33$	Capable	$3 \leq 4$
$1.33 \leq C_P < 1.5$	Satisfactory	$4 \leq 4.5$
$1.50 \leq C_P < 2.00$	Excellent	$4.5 \leq 6$
≥ 2	Super	≥ 6

The following equation describesthe relationship between capability process index and sigma level:

$$\text{Levels of Sigma } \sigma_{L} = 3 \times C_{P} \qquad (9)$$

Table 1 depicts the effect of the capacity process index and sigma level on advanced sigma levels in both industrial and service operations.

4. Sigma levels in the long and short term

Equation may be used to calculate the standard deviation of a method with two-sided specifications (10). The distance and description of Six Sigma are different between the two requirements in this case. SD can be measured using the two-sided method by splitting the design into upper and lower requirements, as shown in the diagram (*USL-LSL*).

$$Z = \frac{\mathrm{USL} - \mathrm{LSL}}{2\sigma} \qquad (10)$$

Standard deviations are divided into two categories: short-term estimators σ_{ST} and long-term estimators σ_{LT}, which can be calculated using the following equations:

$$Z_{ST} = \frac{\mathrm{USL} - \mathrm{LSL}}{2\sigma_{ST}} \qquad (11)$$

and

$$Z_{LT} = \frac{\mathrm{USL} - \mathrm{LSL}}{2\sigma_{LT}} \qquad (12)$$

The following is the mathematical relationship between Z_{ST} and Z_{LT}:

$$Z_{LT} = Z_{ST} + 1.5 \qquad (13)$$

The factor 1.5 reflects the expectation that the mechanism will change 1.5σ in the longer term, as seen in Equation (13). First the 1.5σ shift has no theoretical basis. Second, Equations (11) and (12) reflect the conceptual differences between σ_{LT} and the measured values of Z_{ST} and Z_{LT}, respectively. To better understand σ_{LT} and σ_{ST}, the definition of rational subgroups and variations within subgroups in relation to overall variations should be emphasized. The relationship between Z_{LT} and Z_{ST} can be calculated using these principles. The standard deviation σ_{ST} of a process containing subgroups can be estimated using the aforementioned models in Equations (2), (3), (4), (5), and (6) when data is collected using subgroups and the average and range of subgroups are determined (6). As a result, Z_{ST} reflects process efficiency, and shifts and/or drifts in the process could be removed. This parameter is comparable to the difference between C_p and

C_{pk} capability indices. Process potential is measured by C_p, and process efficiency is measured by C_{pk}. As a result, Z_{ST} denotes the process potential. Centered on the estimators in Equations (2) to (6) of σ, the following expressions are C_p estimators:

$$\hat{C}_P = \frac{USL-LSL}{6\hat{\sigma}_R} \quad (14),$$

$$\hat{C}_P = \frac{USL-LSL}{6\hat{\sigma}_s} \quad (15),$$

$$\hat{C}_P = \frac{USL-LSL}{6\hat{\sigma}_{s_i}} \quad (16),$$

$$\hat{C}_P = \frac{USL-LSL}{6\hat{\sigma}_{w_i}} \quad (17),$$

$$\hat{C}_P = \frac{USL-LSL}{6\hat{\sigma}_{h_i}}. \quad (18)$$

All data from the sub-groups can be used to estimate Z_{LT}. The deviations of each value from the averaged values of the subgroups are computed in this method of calculation, which can be managed and modified using the C_4 constant factor in relation to the subgroup size.

In this case, capacity indices can be calculated using long-term estimation, while variability shows the process's drift using short-term estimation. The assumption that the process moves by $1.5\ \sigma$ to the objective can be used to calculate long-term drift.Long-term differences are assessed using the definition of rational subgroups. In this case, it is presumed that variability within a group is lower than variability between groups [Group σ^2 total $=\sigma^2$ within $+\sigma^2$ within]. This approach can be used to quantify the processes' short-term fluctuations and long-term drift. P_P and P_{pk} are two of the in-dices (Muraliidhran 2015). P_P The index is calculated using the C_p equation, with the exception that pp uses the long-term standard deviation while C_p uses the short-term standard deviation. This parameter's definition is as follows:

$$P_P = \frac{USL - LSL}{6\sigma_{LT}} \quad (19)$$

The difference between P_{PK} and C_{PK} is that P_{PK} uses the long-term standard deviation while C_{PK} uses the short-term standard deviation. This value is determined by.

$$P_{PK} = \min \text{ of } (P_{pu}, P_{pl}) \qquad (20)$$

where $P_{pl} = \dfrac{\overline{\overline{X}} - LSL}{3\sigma_{TL}}, P_{pu} \dfrac{USL - \overline{\overline{X}}}{3\sigma_{TL}}$. σ_{TL} is the long-term sigma value of the process described in Equation (1).

5. Design of $\overline{X}$ Control Chart

Generally, a manufacturing process operates in an in-control state, producing an output product for a relatively long period of time. However, assignable causes occur at random and cause a shift in the process to an out-of-control state where a large proportion of the process out-put does not conform to the specifications.

The primary objective of a control chart is to quickly identify the occurrence of assignable cause(s) so that the process can be examined and corrective action taken before a large number of nonconforming units are generated. The sample size n, the time interval between samples h, and the control limits k must all be chosen before using a Shewhart control chart. It is supposed that n is dimensionless, k is a multiple of the statistic plotted on the chart's standard deviation, and h is in hours. The configuration of the control chart is the selection of (n, h, and k). Duncan (1956) estimated the total net income of a process being tracked by an X-bar chart when the process is subject to a random change in the process mean due to the occurrence of a single assignable cause at a rate of (λ) per hour according to the Poisson distribution. With assumes the process is not shut down while the assignable cause is being investigated, and that the cost of restoring power to the process is not taken into account. The process is assumed to begin in i, n a statistical control condition, with the mean (μ) and standard deviation σ (F. A. M. Ali & Ahmed, 2017). The control chart's center line is held at the process's mean (μ0), the uppe and lower control limits of the process are.

$$\mu + k\frac{\sigma}{\sqrt{n}} \text{ and } \mu - k\frac{\sigma}{\sqrt{n}} \qquad (21)$$

Respectfully, when the process is under control, false alarms will occur at a rate of α, which is the reciprocal of the average run length under control and is expressed as:

$$\alpha = 2\int_{k}^{\infty} \phi(z)dz \qquad (22)$$

Where Φ (z) is the typical normal Vapor Pressure At random, the process could be disrupted by an assignable cause occurring at a rate of λ according to the exponential distribution. The power of detecting process change in any subsequent sample is: If the shift in process mean is $\delta\sigma$, the power of detecting process shift in any subsequent sample is:

$$p = 1-\beta,= \int_{\infty}^{-k-\delta\sqrt{n}} \Phi(z)dz + \int_{-k-\delta\sqrt{n}}^{\infty} \Phi(z)dz \qquad (23)$$

The hunt for the assigna because begins without stopping the process once the control chart defines the shift in the process mean by plotting a point beyond either the upper or lower control limit. A development cycle is divided into four stages:

I. in control
II. The time it takes to produce an out-of-control signal
II. The time it takes takes to produce an out-of-control signal
IV. The quest for and removal of assignable triggers.

5.1 Six Sigma with $\overline{X}$ control chart

When the process parameters, μ— mean and σ — standard deviation, are unknown in statistical quality control based on Shewhart 1931, they are calculated as $\hat{\mu}$ and $\hat{\sigma}$ from sample data obtained from the refinery. The conventional control limits $\hat{\mu}$ $\pm 3\,\hat{\sigma}$ $/\sqrt{n}$ of the study, according to Schoonhoven et al. (2009), provide different performances than the control limit $\mu \pm 3\sigma / \sqrt{n}$ employed for sample means. Control limits can be corrected in this case by replacing the set constant 3 with $\hat{\mu} \pm c(n,k,h)\hat{\sigma} / \sqrt{n}$ and $\hat{\mu} \mp c(n,k,h)\hat{\sigma} / \sqrt{n}$ control limits, where $c(n,k,h)$ denotes the dependent factor on the number of out-of-control signals h. We plan to use 4.5 sigma to estimate the upper and lower control limits of the oil refining process in this study because 3 sigma estimation is inadequate. Despite the fact that there are a number of estimation approaches, studies have shown that 4.5 sigma is efficient at reducing variance and thus improving process efficiency (Chakraborti et al. 2008; Schoonhoven et al. 2009 ; Ravichandran 2016; Ali, Ghaffar, Al-Swidi, & Ahmad, 2021; and Almazah, Ali, Eltayeb, & Atta, 2021). Control limits can be determined using the following mathematical expression, given k as the sample size of n and 4 items with means $\bar{x}_1, \bar{x}_2, \bar{x}_3, \ldots \bar{x}_k$

$$\hat{\mu} \pm z\alpha\left(k\right)\hat{\sigma}_{SS}/\sqrt{n} \qquad (24)$$

where $\hat{\mu} = \frac{1}{k}\sum_{i=1}^{k}\bar{x}_i$, $\bar{X}_i = \frac{1}{n}\sum_{j=1}^{n} x_{ij}$, x_{ij} is the jth observation of ith sample

$$P\left[(-Z_{\alpha}(k) \le Z \le (+Z_{\alpha}(k)\right]1-\alpha_k \qquad 25)$$

The regular normal variate is denoted by the Z. The current Sigma Quality Level (SQL) at which the process should be managed is represented by k . If k = 6, for example, the DPMO 3.4 is either on the left or right tail. As a consequence, $\alpha_{kc} = (6.8)10^{-6}$ implies $Z_{\alpha}(k) = 4.5$, in (1), $\hat{\sigma}_{SS}/\sqrt{n}$ is the approximate standard deviation associated with $\hat{\mu}$ from the Six Sigma Consistency perceptional definition (SSQ) Almazah, et.al 2021. The following procedure can be used to obtain $\hat{\sigma}_{ss}$ from the perspective statistical SSQ: assume that X is a measurable characteristic, so the normal process consists of mean $T = \mu$ and variance σ^2.

Meanwhile, the measurable characteristic denoted by X includes values in the form $T \pm k\sigma$, where T denotes a target or population mean, k denotes a positive constant, and σ denotes the population standard deviation.

As a result: X~ $N(T,\sigma^2)$ $and\ p\ (T - k\sigma \le X \le T + k\sigma.) = 1 - \alpha_k$, where α_k is the predetermined probability value in which $\alpha_k = p(X < T - k\sigma) + p(X > T + k\sigma)$. Based on $T \pm k\sigma$ half of the process spread can be calculated as $k\sigma = d$ indicating $\sigma = d/k$, thus, $\hat{\sigma}_{SS} = d/k$ and we have $\frac{\sigma_{SS}}{\sqrt{n}} = \frac{d/k}{\sqrt{n}}$ the (d) is set according to this equation; as the constant (k) increases, the Sigma(σ)decreases, and vice versa Ali, F. A., et al 2021. As a consequence, the constant k is the process' SQL in terms of the quality characteristic X. The specification limit $T - k\sigma$ is the LSL, and the specification limit $T + k\sigma$ is the USL. As a result, the required Six Sigma-based control limit for a typical SSQ process is: k = 6 and $\hat{\sigma}_{SS} = d/6$.

$$\hat{\mu} \pm (4.5)\left(\frac{\hat{\sigma}_{SS}}{\sqrt{n}}\right) = \hat{\mu} \pm (4.5)\left(\frac{d/6}{\sqrt{n}}\right) \qquad (26)$$

A displacement (shift) occurs in the average by ± 1.5 times the standard deviation over a long period of time, McFadden 1993. As a result, the change also results in 3.4 DPMO, which is the defect low limit. As a consequence, if the approximate mean $\hat{\mu}$ is within $T \pm 1.5\sigma$, process shift is called under control, and the target range is $T \pm 1.5\sigma$. (Ravichandran 2006). Based on Six Sigma $k = 6;$, hence, $3.4\times10^{-6} = P(X \geq T + 6\sigma)$ $and\ P(X \leq T - 6\sigma)0.1*10^{-9}$ if the shift is on the right side $(i.e., T \leq \hat{\mu} \leq T + 1.5\sigma)$ and $3.4x10^{-6} = p(X \leq T - 6\sigma)$ if it is on the left side (i.e., $T - 1.5\sigma \leq \hat{\mu} \leq T$). T. T-1.5 (i.e., if $T = \hat{\mu}$, the mechanism is referred to as centered). As a result, we have $1*10^{-9} = P(X \geq T + 6\sigma)$ finally, separate SQL can be used to calculate the values of $Z_{\alpha}(k)$. The quality standard is $k = 3.$ if the process is level at Three Sigma. The efficiency level is $k = 6$ if the process is running at Six Sigma. The 3 Sigma process's permissible change could result in 66810.63 DPMO. In addition, if the Six Sigma shift happens, the DPMO result would be 3.4. As a consequence of Six Sigma, errors are reduced and the process is of high quality.

6. Controls on Petroleum Derivatives in Aden Refinery

Controlling oil products (petroleum derivatives) is a highly precise and complex process that involves many key stages. Quality control is carried out separately for each product in Aden's oil refinery, and it is normally done in several stages. A sample of oil is taken every 8 hours from each tank at three different locations namely, the upper, the middle and the bottom sections of the tank.

i. Controlling oil products (petroleum derivatives) is a highly precise and complex process that involves many key stages. Quality control is carried out separately for each product in Aden's oil refinery, and it is normally done in several stages.

ii. Results comparison: After the previous tests have been completed and registered, each final value (the product of the measurement) is compared to the international and domestic standard for each test. The procedure is performed in a min and max range in this scenario. Since most tests do not have super or small output values, only values between the min and max are available.

Controlling a specific product entails having control over a collection of physical properties for the product, which are then used to assess its efficiency. As a result, the gasoline characteristic and vapor pressure are used in this case to determine the consistency of the oil product in the Aden refinery. The following is an example of this characteristic.

6.1 Characteristics of Vapor Pressure

The vapor pressure is known at a specific temperature. Every material having a higher vapor pressure is generally more likely to be combustible and to explode. When a liquid reaches its boiling point, it evaporates and the particles start to leave the liquid in the vacuum above it. However, if there is no suction point above the material, at a certain degree those particles reach a maximum, and pressure on the walls of the vessel is equal to atmospheric pressure and vapor-particle pressure. This normally controls the vapor pressure of the gasoline to remain within upper and lower criteria of 7 and 10 correspondingly. The vapor pressure of oil products varies widely between countries. It is important to note that lower vapor pressure levels (under the lower standard limit) make it difficult for machinery to start or autos.

6.2 Assessment of Aden Refinery's Current Output

The first step to evaluating the status of each industry's process efficiency is to measure present performance. There are different methods to evaluate the present efficiency of the operation. The bulk of these measurements have been assessed using a range of procedures which lead to a diversity of results. Therefore, it is necessary to employ correct methods of estimation and measurement when measuring the effectiveness of the process. The purpose of this research is to produce special measurement and evaluation measures for process performance in industry. This is the topic of several studies. This study thus provides a case study that measures and evaluates the process performance of an oil refinery in Yemen.

6.2.1 Data Collection

This study analyses the commodity of petroleum fuels by examining a vapor pressure, one of its key features. The most important features of all oil products are, without a doubt, these features. For relative vapor pressure data, the following approach is used: Initially, the oil selections are taken at a random rate in three separate sites: the upper, middle, and lower area of the tanks using the petroleum hydrometer. The sample will be mixed together as the density levels fluctuate between different tank sites. After the sample is mixed, three features, one of which is vapor pressure, are examined in the laboratory. Adequate data from the whole population must be collected from the survey. In this study, 50 samples (See Appendix: A) (each sample containing four items) of oil Vapor Pressure in Aden oil refinery were randomly selected., the selection of a sample implies a number of key issues, including the capacity and appropriateness, accuracy and consistent statistical analysis of the sample to represent the actual population. Significant statistical tests are conducted for further investigation following the gathering of data, related to validation. The normalcy test, the stationary test, autocorrelation and heteroscedasticity tests, as well as the process capacity test, are included.

I. Normality Test

Table 2 shows the consequencesq of the univariate vapor pressure normalcy test. The statistical analyzes Kolmogorov-Smirnov and Shapiro-Wilk both have p-values over 5%, which show that vapor pressure is normal. The vapor pressure is also significant, which shows that it is statistically correct and sufficient for future research. The p.value over the 5 % level of significance hence accepts the null-hypothesis. The skews are also between (+1/2) and (-1/2), which means that the distribution of the d is substantially symmetrical.

Table 2 Shows the results of the tests normality for the Vapor Pressure Characteristic.

	Kolmogorov-Smirnov[a]		Shapiro,Wilk	
	Statistic	P. value.	Statistic	P.value.
Vapor Pressure	0.067	0.038	0.988	0.089

II. Stability of the Process (unit root)

Table 3 displays the findings of the unit root assessment (Augmented Dicky-Fuller). The series is assessed constantly, based on the frequency of the data the best lag is determined. According to Brooks (2014), experiments on the number of lags of residues with a number of values are typical and data frequency can be employed for the number selection. In this vein, the review continues. T-statistics were larger than their critical value, and all the observed variables were integrated at 5% significance in order zero or stationary with the I(0) phase. The findings show that no unit root is available in the studied series.

Table 3 Shows the impacts of the phase and first difference ADF root test unit.

Variable	T-Statistics(Level)	T-Statistics (First Difference)	Order of integration
Vapor P	-5.03(8)**	-6.80(8)	I(0)

Notes: MacKinnon (1996) calculated critical values of -4.00, -3.43, and -3.14 at the 1%, 5%, and 10% stages, respectively. 2. A 5% degree of significance is indicated by a **.

III. Autoregressive Test

In order to study the data properties, the research is enlarged to review the fundamental statistical testing that was related with the single-variate self-regressive model. The measurements applied individually to the underlying sequence are normality and autocorrelation. The findings are summarized in Table 4.

Table 4: Results of statistical tests based on the autoregressive model

Series	Statistic-Tests		
	Statistic *JB*	*LM* Statistic	*H* Statistic
Vapor P	0.16(0.71)	0.37(0.75)	3.06(0.09)

Notes: statistics JB, LM & H refers to a normality test of Jarque Bera (1990), a Lagrange Lagrange Multiplier test of Breusch -Godfrey Serial Correlation, a 1978 and a heteroskedasticity test for Engle (1982), respectively. The results of the vapor pressure autoregressive model are as show in Table 4 is the Jarque-Bera normality test for residues with one degree of freedom. The JB-test statistical value was 0.16 respectively for vapor pressure. These results are less than the crucial value of 4.40, with a 5% importance. This feature is not statistically important, since the p-values above the level of 5%. (% 0.71). The conclusion was therefore formed that the residual vapor pressure series were regularly distributed.

6.3 S-Deviation Estimators by Control Charts

Standard vapor pressure and vapor stress variances are computed using equations (2-6) by means of control charts and the results are shown in the Table (5).

6.4 Estimation of Process Capability

The types of estimators used to measure the standard deviation are used to estimate process capacity. PCIs are calculated in this study using common estimators and control chart-based PCI estimators.

6.4.1 PCI Estimators in General

For the characteristic vapor pressure, popular PCI estimators are used.

2.4.1.1 Estimated PCIs for Vapor Pressure

Equations (1) and (6) can be used to measure the

$$C_p = \frac{U-L}{6\sigma_{LT}} = \frac{10-7}{6(1.89253)} = 0.26539 \qquad (27)$$

If C_p is less than one, the process variance exceeds the defined tolerances.

Equations (1) and (8) can be used to measure the $\hat{C}_{pk}$ as follows:

$$C_{pk} = \min\left[\frac{(\mathrm{U}-\overline{\overline{\mathrm{X}}})}{3\sigma_{\mathrm{LT}}}, \frac{(\overline{\overline{\mathrm{X}}}-\mathrm{L})}{3\sigma_{LT}}\right] =$$

$$= \min\left[\frac{10-8.295}{3\times1.89253}, \frac{8.2935-7}{3\times1.89253}\right] \qquad (28)$$

$$= \min\,(0.30087,\ 0.22891) = 0.22891$$

6.4.2 PCIs estimators based on control charts S.D. for vapor pressure

$\hat{\sigma}_R$ can be used to calculate the PCIs by combining Equation (2) with Equations (7) and (8) as follows:

$$\hat{C}_p = \frac{10-7}{(6\times 0.33129)} = 1.5096 \qquad (29)$$

$$\hat{C}_{pk} = \min\left[\frac{USL-\overline{\overline{X}}}{3\hat{\sigma}_R}, \frac{\overline{\overline{X}}-LSL}{3\hat{\sigma}_R}\right]$$

$$= \min\left[\frac{10-8.2945}{3(0.33129)}, \frac{8.2945-7}{3(0.33129)}\right] \qquad (30)$$

$$= \min[\ 1.302,\ 1.717\ ] = 1.302$$

and

$$\hat{C}_{pm} = \frac{D}{6\sqrt{\sigma^2+\delta^2}} = \frac{3}{2.341959} = 1.28098 \qquad (31)$$

The PCIs can be calculated by Equation (3) with Equation (7) and Equation (8) the following:

$$\hat{C}_p = \frac{3}{(6\times 0.315661)} = 1.57398 \qquad (32)$$

$$\hat{C}_{pk} = \min\left[\frac{USL-\overline{\overline{X}}}{3\hat{\sigma}_S}, \frac{\overline{\overline{X}}-LSL}{3\hat{\sigma}_S}\right]$$

$$= \min\left[\frac{10-8.2935}{3(0.315661)}, \frac{8.2935-7}{3(0.315661)}\right] \qquad (33)$$

$$= \min[1.802039\ ,\ 1.365917\ ] = 1.36592$$

And

$$\hat{C}_{pm} = \frac{D}{6\sqrt{\sigma^2+\delta^2}} = \frac{3}{2.263233} = 1.32554 \qquad (34)$$

$\hat{\sigma}_{S_l}$ Can be used to calculate PCIs by combining Equation (4) with Equations (7) and (8) as follows:

$$\hat{C}_p = \frac{3}{(6*0.318978)} = 1.56751 \qquad (35)$$

$$\hat{C}_{pk} = \min\left[\frac{U-\overline{\overline{X}}}{3\hat{\sigma}_{s_i}}, \frac{\overline{\overline{X}}-L}{3\hat{\sigma}_{s_i}}\right]$$
$$= \min\left[\frac{10-8.2935}{3(0.318978)}, \frac{8.2935-7}{3(0.318978)}\right] \quad (36)$$
$$= \min[1.783298, 1.351712] = 1.35171$$

and

$$\hat{C}_{pm} = \frac{D}{6\sqrt{\sigma^2+\delta^2}} = \frac{3}{2.279916} = 1.31584 \quad (37)$$

$\hat{\sigma}_{wi}$ Can be used to calculate the PCIs by combining Equation (5) with Equations (7,8) as follows:

$$\hat{C}_p = \frac{3}{6\times 0.33129} = 1.50953 \quad (38)$$

$$\hat{C}_{pk} = \min\left[\frac{U-\overline{\overline{X}}}{3\hat{\sigma}_{wi}}, \frac{\overline{\overline{X}}-L}{3\hat{\sigma}_{wi}}\right]$$
$$= \min\left[\frac{10-8.2935}{0.993686}, \frac{1.2935}{0.993686}\right] \quad (39)$$
$$= \min[1.717343, 1.301719] = 1.30172$$

(41) $$\hat{C}_{pm} = \frac{D}{6\sqrt{\sigma^2+\delta^2}} = \frac{3}{2.341959} = 1.28098$$

$\hat{\sigma}_{hi}$ Can be used to calculate the PCIs by combining Equation (6) with Equations (7,8) as follows:

$$\hat{C}_p = \frac{3}{2.034373248} = 1.47466 \quad (40)$$

$$\hat{C}_{pk} = \min\left[\frac{U-\overline{\overline{X}}}{3\hat{\sigma}_{hi}}, \frac{\overline{\overline{X}}-L}{3\hat{\sigma}_{hi}}\right]$$
$$= \min\left[\frac{10-8.2935}{1.017186624}, \frac{1.2935}{1.017186624}\right] \quad (41)$$
$$= \min[1.677666576, 1.27164472] = 1.27166$$

$$\hat{C}_{pm} = \frac{D}{6\sqrt{\sigma^2 + \delta^2}} = \frac{3}{2.381973} = 1.259 \qquad (42)$$

6.5 Discussion for Characteristic of Vapor Pressure

For vapor pressure characteristic, the current process performance results are presented in Table 5. The displayed results are based on univariate process capability indices namely C_p, C_{pk} and Table 5 displays the latest process efficiency results for the vapor pressure characteristic. The displayed results are focused on uni-variate process capacity indices, such as C_{pm}, which are based on sigma estimation. It can be seen that the oil gasoline refinery's process output for the vapor pressure characteristic does not follow the predefined specifications. This conclusion is based on the C_p, C_{pk} and C_{pm} as well as the values in Table 5. For example, the long-term value of C_p is 0.27, which is less than 1. The value of C_{pk}, which is less than 1.5 in all estimations, is consistent with this. Aside from that, the value of C_p, C_{pk} and C_{pm} has changed as different methods of estimating the standard deviation $\hat{\sigma}_{LT}, \hat{\sigma}_R, \hat{\sigma}_{Si}, \hat{\sigma}_{S}, \hat{\sigma}_{wi}$ and $\hat{\sigma}_{hi}$ have been created. As a result, it is clear that various estimates of process standard deviation have affected the C_p, C_{pk} and C_{pm} values, and thus the overall process capacity. The Six Sigma principle based on control limits can be used to assess the statistical accuracy of the process capability. Thus, using Equation (26), sigma is determined for the vapor pressure characteristic using $\bar{X}$ chart control based on the upper and lower control limits as follows:

$$\hat{\mu} \pm (4.5)\left(\frac{\hat{\sigma}_{SS}}{\sqrt{n}}\right) = 8.295 \pm \frac{(4.5)(0.25)}{\sqrt{4}} \qquad (43)$$
$$\rightarrow UCL = 8.856 \text{ }, LCL = 7.731$$

The sigma-based and traditional $\bar{X}$ control table, as well as the level sigma with lower and upper control limits, are shown in Figure 1. Because of points that are outside of the control limits, the vapor pressure characteristic is not in line with the statistical control, as seen in (1), (2), (3), (5), (7), (21), (22), (23), (24), (25), and (26). Furthermore, the level sigma for the vapor pressure characteristic can be calculated using the following relationship between capability method and level sigma:

$$L\sigma = 3 \times C_p = 1.5739 \times 3 = 4.175194$$
$$l\sigma = 3 \times C_p = 0.2744 \times 3 = 0.8232 \quad (44)$$

Standard deviation allows the C_p index to have different values, according to Equations (44). As a result, when the values of C_p are changed, the sigma amount changes. The sigma level differs between 0.82 and 4.175.

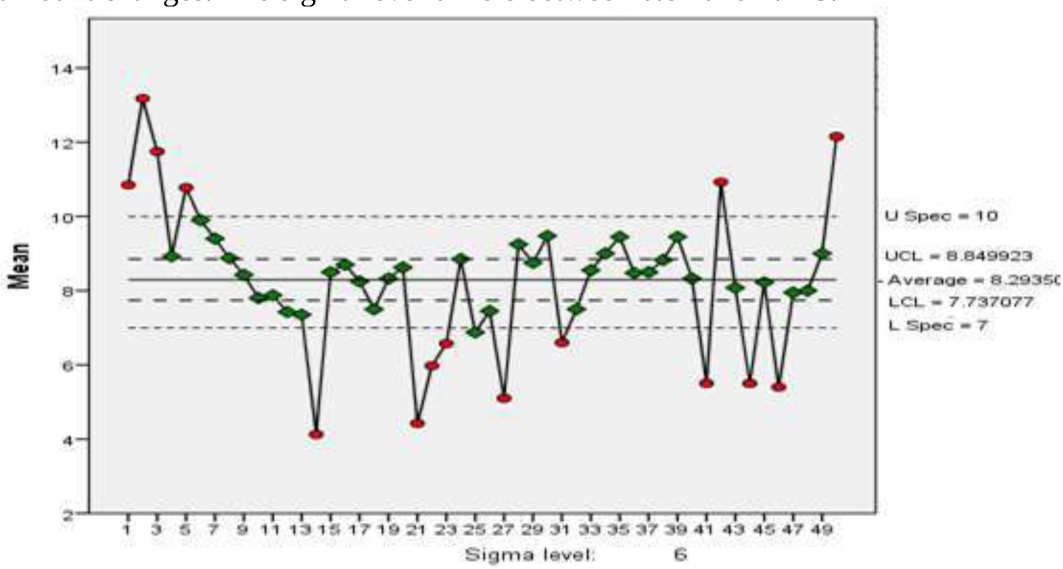

Figure 1: Sigma with X-bar control chart for vapor pressure characteristic

Table 5: The obtained PCIs with different methods for estimating standard deviation of oil vapor pressure characteristic

Indices	$\hat{\sigma}_{LT}$	$\hat{\sigma}_R$	$\hat{\sigma}_s$	$\hat{\sigma}_{si}$	$\hat{\sigma}_{wi}$	$\hat{\sigma}_{hi}$
$\hat{C}_p$	0.27	1.509	1.574	1.567	1.509	1.477
$\hat{C}_{pk}$	0.23	1.302	1.369	1.357	1.302	1.276
$\hat{C}_{pm}$	0.24	1.280	1.325	1.318	1.281	1.259
S.D	2.02	0.331	0.316	0.319	0.331	0.339

Based on the above, the present level sigma of the vapor pressure characteristic in the Aden refinery is 4.175. In this case, the capability process is equivalent to 1.57, which is the refinery's highest defined amount. At $C_p = 1.57$ the value index method capability As a consequence, major improvements in standard deviation measurement methods have an effect on the sigma level and process capacity. As a consequence, standard deviation can be measured using method $\hat{\sigma}_s$, which has a low variance of 0.3156608 and thus increases the sigma level and process capacity.

Furthermore, the recalculated value of the standard deviation at $4\sigma, 5\sigma$, and 6σ with $\bar{X}$ control chart with respect to the lower and upper control limits for the process by using Equation (26) the formula for measuring the standard deviation of the process provides a significant solution to reduce variations based on the process's limits and specifications provides a significant solution to reduce variations based on the process's limits and specifications provides a significant solution to reduce variations based on the process's limits and specifications. The method may also measure the values of the lower and upper limits in relation to the capacity process's pre-specified limits. As a result, using the Six Sigma principle, a method for calculating the process' standard deviation has been successfully established. The difference between the upper and lower specification limits for oil vapor pressure is $U - L = 3$ according to Equation (26). As the sigma levels change, the value ofchanges. As a result, for advanced levels of sigma k, we can measure the control limits and standard deviation, as 6σ and $4\sigma, 5\sigma$ shown in Table 6.

Table 6: Vapor pressure characteristic control limits and S.D at level sigma

$L\sigma$	$\hat{\sigma}_{SS}$	UCL	LCL
4σ	0.375	9.13725	7.44975
5σ	0.30	8.9685	7.6185
6σ	0.25	8.856	7.731

Figure 2 shows how the process capability improves when the refinery uses advanced levels of sigma, such as $4\sigma, 5\sigma$ and 6σ for the vapor pressure characteristic.

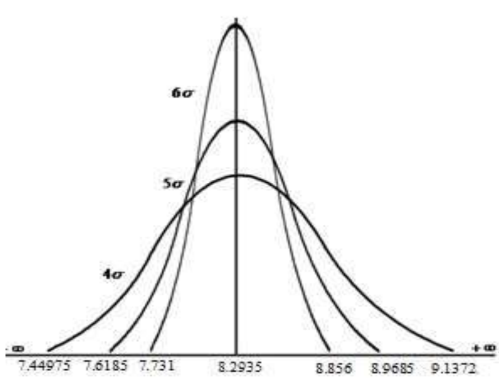

Figure 2: Process capacity for vapor pressure characteristic at level sigma $4\sigma, 5\sigma$ and 6σ

7. Conclusions

In several businesses and industries, Six Sigma is a quality improvement tool. This article aims to use Six Sigma to enhance oil production process capability in Yemen. The oil manufacturing technique Vapor Pressure is utilized for this purpose. This research also seeks to improve the performance of the oil vapor pressure capability method by decreasing process variability. Changes frequently influence the process performance and suggest that it is out of control. The standard process deviation is measured by the influence of several approaches to calculate standard deviation using PCI estimates. 25 samples of vapor pressure oil were randomly selected in this study (each sample contains four items). We have collected data from the refinery to analyze the level of sigma used in oil production in Aden oil refinery in Yemen. Data analyzes using Minitab and SAS software have been conducted. The results showed that the sigma level of less than four sigma used in the Aden oil refinery. Therefore, oil production must increase its process performance. Considering the substantial link between Sigma level and process capacity, Six Sigma is available to improve and regulate process performance of oil production in Yemen. Therefore, 6σ is an important PCI notion. These indices come from SPC, a statistically effective method used to check production processes. This is a very effective instrument. The process limit of ±3σ relates to the rate of defection 27/1000 or process opportunities 2700/1000000. In addition to this, the results show a decrease of variations if the process limit range of ±3σ is doubled to ±6σ, which allows the lateral shift of 1.5σ the process average. The results achieved with the sigma levels thus represent a dramatically acceptable target of defects. This study compared the standard deviation for vapor pressure oil characteristic by three distinct approaches. These approaches are the long-term estimation of the method and the $\overline{X}$ chart evaluation method based on control charts, the short-term estimation and a common method of estimation. The $\overline{X}$ chart estimation method has been obtained from the analysis, since this approach is estimated according to specified restrictions. The overall findings show that by increasing the sigma level, the processing capacity of oil refining vapor pressure may be enhanced. Hence, if the level of Sigma is 5σ, the process capacity differs between the C_P values (1.67-1.56) = 0.11%. In this scenario, when the refinery employs 5σ, the C_P value increases from 1.56 to 1.67. Finally, when the level of Sigma is at 6σ, the capacity equals the difference of (2-1.56) = 44% between the C_P values. In that scenario, when the refinery employs 6σ, C_P value is increased from 1.56 to 2, process performance is increased to 44 %.

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Appendix: A

TABLE 1. Sample of the data collected for the oil's Oil Vapor Pressure characteristic.

NO	X_1	X_2	X_3	X_4	NO	X_1	X_2	X_3	X_4
1	10.5	10.4	11	11.5	26	7.5	8.5	7.4	6.4
2	14	12.5	12.7	13.5	27	5	4.5	5.5	5.4
3	10.2	13.5	12.5	10.8	28	8.7	9.7	9	9.6
4	10.9	8.5	8.3	8	29	8.3	9.4	8.8	8.5
5	10	13	10.4	9.7	30	8	10.9	8.6	10.4
6	10.6	7.7	10.3	11	31	5	7.5	7.2	6.7
7	10.9	8.5	8.7	9.5	32	8.8	8.5	6.8	5.9
8	11	8.4	7.7	8.4	33	7.8	7.9	9	9.5
9	9.4	8.3	7.6	8.4	34	10	7.8	9.9	8.3
10	8.6	8.5	7.2	6.9	35	8.5	11	8.5	9.8
11	6.5	8.5	8.3	8.2	36	7.6	9	8	9.3
12	6.9	8.2	8.2	6.4	37	8	9.9	7.6	8.5
13	8.4	8.2	5.8	7	38	8.5	9.8	7.3	9.7
14	4.5	5.4	3	3.6	39	9.7	7.6	11.5	9
15	7.5	8.8	7.8	9.9	40	8.7	9.9	6	8.7
16	7.3	8.8	8.8	9.9	41	5.5	4.7	6.4	5.4
17	7.7	8.9	8.7	7.7	42	12.5	11.3	10	9.9
18	6.9	7.7	8.5	6.9	43	7.9	8	8.8	7.6
19	6.9	8.2	8.6	9.6	44	4.8	4	6.3	6.9
20	7	9.8	9	8.7	45	8.5	9.4	8	7
21	4.6	3.5	5.6	4	46	5.4	4.9	6.3	5
22	6.9	4.9	5.4	6.7	47	8.8	7.6	6.4	9
23	6.7	6.6	7	6	48	8.5	8	9.8	5.7
24	7.6	10	8.3	9.5	49	7.9	8.6	9.9	9.6
25	7	7.8	5.7	7	50	10.8	13	12	12.8

Aden Refinery 2016