

Modified SPC for short run test and measurement process in multi-stations

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Abstract. Due to short production runs and measurement error inherent in electronic test and measurement (T&M) processes, continuous quality monitoring through real-time statistical process control (SPC) is challenging. Industry practice allows the installation of guard band using measurement uncertainty to reduce the width of acceptance limit, as an indirect way to compensate the measurement errors. This paper presents a new SPC model combining modified guard band and control charts (\bar{Z} chart and W chart) for short runs in T&M process in multi-stations. The proposed model standardizes the observed value with measurement target (T) and rationed measurement uncertainty (U). S-factor (S_f) is introduced to the control limits to improve the sensitivity in detecting small shifts. The model was embedded in automated quality control system and verified with a case study in real industry.

1. Introduction

The key characteristics of test and measurement (T&M) manufacturing are short production runs of multi-product families and testing at multi-stations. Classical Shewhart control charts, namely \bar{x} chart and R chart have been widely used in statistical process control (SPC) to detect process variable shifts in mean and variance [1]. Short production runs render these charts inefficacious as inherent meager data do not warrant meaningful control limits [2]. Furthermore, Costa and Castagliola [3] underscore the problem of growing risk of false acceptance in SPC due to measurement error. This leads to consequences such as unnecessary process adjustment and loss of confidence in SPC.

In these premises, this research proposes a modified SPC model which combines modified guard band and control charts (\bar{Z} chart and W chart) to address the issues caused by short production runs and measurement errors. The proposed model standardizes the observed value with measurement target (T) and rationed measurement uncertainty (U). The organization of the paper is as follow: A review of the literature of measurement uncertainty and short run techniques and will be presented in the next section. The proposed model and the industrial case study are described in section 3 and section 4 respectively. Section 5 discusses the results obtained from the case study. Finally, section 6 draws conclusion.



2. Literature Review

2.1. Short Run approaches

Several short run charts have been proposed using statistics techniques such as difference chart, DNOM (deviation from nominal) chart and standardized charts [1,4]. Difference chart (also called X-nominal) registers differences between the mean to its nominal/target value [5]. DNOM chart is based on ratios of subgroup means to nominal [6]. Useful in a scenario with shifting variances, standardized charts with short runs techniques was proposed by Bothe [2] to revise the target value proportionally to the amount of dispersion from product to product. It allows the operator to plot different product families on a single \bar{x} chart and R chart.

Wheeler [5] extends the approach using the Z chart (also called Zed chart) and W chart to measure central tendency and dispersion respectively. Consider a process where x_{ij} represents the i th response on the j th part family member, $i = 1, \dots, m$, and $j = 1, \dots, p$. The process response is normalized using an estimate of the population standard deviation, denoted by $\hat{\sigma}_{x_j}$ as:

$$\hat{\sigma}_{x_j} = \frac{\bar{R}_j}{d_2} \quad (1)$$

where \bar{R}_j is the average range for the j th part family member; d_2 is a statistic constant for subgroup size (n) displaying a normally distributed quality characteristic. The Z_{ij} values for Z chart are then calculated as:

$$Z_{ij} = \frac{x_{ij} - T_j}{\hat{\sigma}_{x_j}} \quad (2)$$

where T_j is the target value for each part family member that can be determined by using historical data, specification, or prior experience on the similar parts [1]. Wheeler [5] introduced \bar{Z} chart (also called Zed bar chart) for subgroup data when $n > 1$. The mean values for \bar{Z} chart is then calculated as:

$$\bar{Z}_{ij} = \frac{\bar{x}_{ij} - T_j}{\hat{\sigma}_{\bar{x}_j}} \quad (3)$$

where $\hat{\sigma}_{\bar{x}_j}$ is an estimate of the population standard deviation of the subgroup mean as:

$$\hat{\sigma}_{\bar{x}_j} = \frac{\bar{R}_j}{d_2 \sqrt{n}} \quad (4)$$

and the ranges, R_{ij} for the W chart are transformed as follows:

$$W_{ij} = \frac{R_{ij}}{\hat{\sigma}_{x_j}} \quad (5)$$

\bar{Z} chart will have a central line at zero with the upper and lower control limits set at +3 and -3, respectively. W chart set its central line at d_2 as $R = \bar{R}$; upper and lower control limits at $d_2 + 3d_3$ and $d_2 - 3d_3$ respectively, where d_3 is a statistic constant for subgroup size (n).

The advantages of \bar{Z} chart and W chart, are that the measured data from multiple product families can be plotted on a single chart and relatively low average run length (ARL) required in comparison to \bar{x} chart and R chart [7]. The disadvantages of \bar{Z} chart and W chart, are that the sigma is often unknown, a separate estimate is usually obtained for each product and this method requires sufficient data to negate the fact that the true parameter values used in the calculation of the control limit estimation [8]. These charts are inefficiently adopted in some T&M processes due to the measured data are affected by measurement error.

2.2. Guard band approaches

The most immediate approach to minimize the measurement errors is by utilizing guard band to reduce the width of acceptance limit. Various economic aspects of guard band have been proposed by several researchers (e.g., [9]) to ensure the acceptable risk decision in the product conformity. Industry practice allows the installation of guard band, e.g., through Guide to the Expression of Uncertainty in

Measurement (GUM), published by ISO in 1993 to reduce the width of acceptance limit [10], as an indirect way to compensate the measurement errors. Incorporation of stringent control as in \bar{Z} chart and W chart into guard band could potentially aid to screen for assignable causes and to detect early quality deterioration in the process.

3. Modified SPC model

3.1. Overview

The model standardizes the observed value in relation to the measurement target (T) and measurement uncertainty (U). Measurement target is referred as an expected value for a predetermined measurement characteristic. The target value is calculated based on repeated measurement with series observations for each test station separately and to be revised when the measurement characteristic changes. Measurement uncertainty refers to the dispersion of the data that could reasonably be attributed to the measurement result [11]. Pythagoras's theorem is used to estimate the process standard deviation with population standard deviation and measurement uncertainty as inputs. S-factor (S_f) is introduced as separate approaches to the control limits to improve the sensitivity in detecting small shifts. Eight tests are proposed to interpret the charts using Nelson's rules.

3.2. Evaluation of measurement uncertainty

Measurement uncertainty will be evaluated using GUM [10], in four steps as follows:

3.2.1. Step 1: Identifying all sources of uncertainty. The first step is to identify the output result, Y , from N input quantities through a function relation f as in equation (6):

$$Y = f(X_1, X_2, \dots, X_N) \quad (6)$$

where X_i is an input quantity that can significantly affect the measurement result. An estimate of the output Y , denoted by y , using input estimates x_1, x_2, \dots, x_N , as shown in equation (7):

$$y = f(x_1, x_2, \dots, x_N) \quad (7)$$

Determining the uncertainty of y requires the uncertainties of all the input estimates x_i referred as standard uncertainties $u(x_i)$.

3.2.2. Step 2: Evaluating the standard uncertainty. The value for $u(x_i)$, could be obtained from either Type A or Type B evaluation. Type A evaluation is characterized by a statistically estimated sample standard deviation s_i , and the associated number of degrees of freedom ν_i . The sample standard deviation of the mean is computed as:

$$u(x_i) = \frac{s_i}{\sqrt{r}} \quad (8)$$

where r was the number of the independent repeated observations. The r should be large enough to ensure the estimated value is reliable that the probability distribution often is assumed to be normal [12].

Type B evaluates a component of measurement uncertainty that has been excluded in Type A evaluation. In the evaluation, $u(x_i)$ refers to an assumed probability distribution based on previous measurement data, input of experienced personnel, manufacturer's specification, data provided in calibration report [13]. Amongst various distributions exist, (e.g., rectangular, triangular, U-shaped, normal.), rectangular distribution is the most common in the analysis of T&M. The accompanying standard measurement uncertainty is:

$$u(x_i) = \frac{a}{\sqrt{3}} \quad (9)$$

where a is the semi-range (or half-width) constant set between the upper and lower limits.

3.2.3. Step 3: Computing the Combined Standard Uncertainty. Combined standard uncertainty, denoted by $u_c(y)$ is compiled from individual $u(x_i)$, using Summation in Quadrature which is often called the law of propagation of measurement uncertainty, as given below:

$$u_c(y) = [\sum_1^n [c_i u(x_i)]^2]^{\frac{1}{2}} \quad (10)$$

where c_i is the sensitivity coefficient associated with x_i . Eq. 10 is valid only if the input quantities X_i are independent or uncorrected. In most cases, input quantity X_i is uncorrelated, and sensitivity coefficient can be assumed to be 1 [14].

3.2.4. Step 4: Computing the Expanded Uncertainty. Originated from GUM, expanded uncertainty, U is calculated by factoring in a coverage factor, k into combined standard uncertainty $u_c(y)$:

$$U = k u_c(y) \quad (11)$$

where k is chosen from the effective degrees of freedom ν of all the uncertainty sources, considering a specified coverage probability, calculated through Student's t-distribution. Most commonly, $k = 2$ is chosen to give a level of confidence of approximately 95% [15]. It is recommended that the expanded uncertainty (U) be rounded normally to two significant figures [12].

The doubt of the measurement can be quantified when the true value is within the margin with U and the confidence level [15]. All measurement uncertainty components regardless of classification are modeled by probability distributions quantified by variances or standard deviations [12]. Therefore, the process standard deviation contributed by measurement error can be estimated using equation (12), which is termed standard deviation of the measurement uncertainty and denoted by $\hat{\sigma}_u$.

$$\hat{\sigma}_u = \frac{U}{k} \quad (12)$$

3.3. Standardized measurement target and measurement uncertainty

The measurement uncertainty is dependent on the accuracy of the equipment used in the individual test station. An equation is formed by extending the equation (3) with m th test station instead of j th part family member. \bar{Z}_{im} for modified \bar{Z} chart takes measurement uncertainty into account, as depicted in equation (13):

$$\bar{Z}_{im} = \frac{\sqrt{n} (\bar{x}_{im} - T_m)}{\hat{\sigma}_{p_m}} \quad (13)$$

where T_m is an expected value of the measurement target and $\hat{\sigma}_{p_m}$ is an estimate of the process standard deviation for each test station. Range for modified W chart are extended from equation (5) as follows:

$$W_{im} = \frac{R_{im}}{\hat{\sigma}_{p_m}} \quad (14)$$

The $\hat{\sigma}_{p_m}$ provides the tolerance for the control limits. The model iteratively expands the tolerance limit from the lowest to highest value of $\hat{\sigma}_{p_m}$. For the lowest values, $\min \hat{\sigma}_{p_m} = \hat{\sigma}_{x_m}$, where $\hat{\sigma}_{x_m}$ is an estimate of the population standard deviation that can be calculated by:

$$\hat{\sigma}_{x_m} = \frac{\bar{R}_m}{d_2} \quad (15)$$

where \bar{R}_m is the average range for the m th test station. For the highest values, $\hat{\sigma}_u$ from equation (12) is taken into account. Pythagoras's theorem is used to estimate the maximum value of the $\hat{\sigma}_{p_m}$, as given below:

$$\max \hat{\sigma}_{p_m} = \sqrt{\hat{\sigma}_{x_m}^2 + \hat{\sigma}_u^2} \quad (16)$$

The central line and control limits of modified charts are fixed with constant values as applied in the \bar{Z} chart and W chart. The charts are interpreted using Nelson's rules as defined in table 1. Rules 1,

2, 5, and 6 are to be applied to upper and lower halves of the chart separately. Rules 3, 4, 7, and 8 are to be applied to whole chart [16]. With this, all rules apply to \bar{x} chart and \bar{Z} chart. However, only rule 1, 2, 5 and 6 can be applied to dispersion chart (R chart and W chart) without modification when the subgroup size is 5 or more which will lead to the symmetric control limits [17].

Table 1. Nelson Rules

Rule	Description
Rule 1	One point is more than 3 standard deviations (σ) from the mean.
Rule 2	Nine points in a row are on the same side of the mean.
Rule 3	Six points in a row are continually increasing (or decreasing).
Rule 4	Fourteen points in a row alternate in direction, increasing then decreasing.
Rule 5	Two out of three points in a row are more than 2σ from the mean in the same direction.
Rule 6	Four out of five points in a row are more than 1σ from the mean in the same direction.
Rule 7	Fifteen points in a row are all within 1σ of the mean on either side of the mean.
Rule 8	Eight points in a row exist with none within 1σ of the mean and the points are in both directions from the mean.

3.4. Determining $\hat{\sigma}_{pm}$ through S-factor

S-factor is an approach to estimate $\hat{\sigma}_{pm}$ is through the expanded uncertainty (U_m) and S-factor (S_{fm}), with the formula set as below:

$$\hat{\sigma}_{pm} = \frac{U_m}{S_{fm}} \quad (17)$$

S-factor is then delineated as the ratio between the highest value of $\hat{\sigma}_{pm}$ and the lowest value of $\hat{\sigma}_{pm}$, is given by:

$$S_{fm} = \frac{\max \hat{\sigma}_{pm}}{\min \hat{\sigma}_{pm}} \quad (18)$$

and the $\hat{\sigma}_{pm}$ is set equal to $\min \hat{\sigma}_{pm}$ when the estimated value of the $\hat{\sigma}_{pm}$ is equal or less than $\hat{\sigma}_{xm}$, where:

$$\min S_{fm} = \frac{U_m}{\hat{\sigma}_{xm}} \quad (19)$$

As shown in figure 1, S-factor is useful to rescales the process standard deviation, and it is dependent on the ratio between the measurement uncertainty and the population standard deviation, which is termed as $U/k\sigma_x$. For example, the $\hat{\sigma}_{pm}$ estimated by S-factor is equal to $\max \hat{\sigma}_{pm}$ when $U/k\sigma_x$ ratio is equal to 1, and it is equal to $\min \hat{\sigma}_{pm}$ when $U/k\sigma_x$ ratio is equal or less than 0.577.

Finally, the \bar{Z}_{im} values for \bar{Z} chart are given by:

$$\bar{Z}_{im} = \frac{\sqrt{n} S_{fm} (x_{im} - T_m)}{U_m} \quad (20)$$

and range values for W chart are transformed using the following formula:

$$W_{im} = \frac{S_{fm} R_{im}}{U_m} \quad (21)$$

3.5. Model implementation

In implementation, the model was embedded in an automated SPC system. The SPC application is developed using Visual Studio to gather data from test record database and to perform data analysis using analysis tool developed by Scrucca [18]. The tool uses R package (open-source programming

language) for quality control charting and violating rules checking. Automated SPC includes four steps: extracting data, creating analysis files, configuring setting and executing the SPC application. Variables used in the model (e.g., T_m , U_m , S_{f_m}) are defined and to be configured at setting stage. Two set of charts are plots, as below:

1. Classical Shewhart control charts (\bar{x} chart and R chart)
2. \bar{Z} chart and W chart with $\hat{\sigma}_{p_m}$ determined through S-factor

Eight tests based on Nelson's rules interpret the charts. False alarm rate is used to compare the performance of the proposed models with classical Shewhart control charts. A false alarm will be counted if the rule test detected when the process behaves as per this normal or in-control behavior.

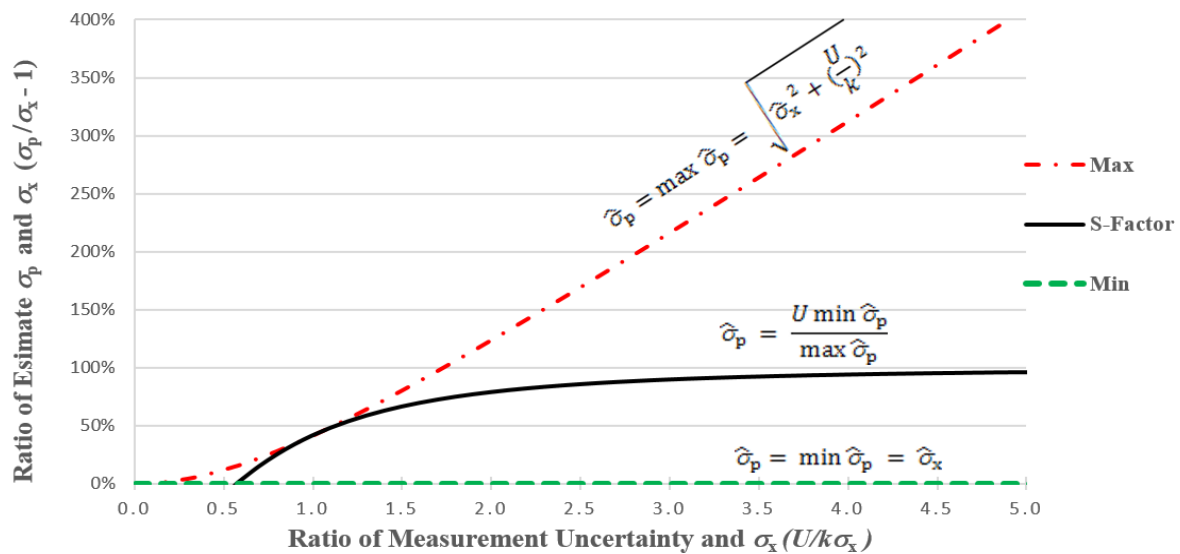


Figure 1. Estimated process standard deviation with S-factor

4. Verification through case study in real industry

A complete year's data samples were collected from a product tested at multi-stations in a T&M manufacturing facility at Bayan Lepas, Penang. The DC vertical gain accuracy (VGA) for oscilloscope test is selected where it consists of 700 measurement results tested at three stations (WH05, WH06, and WH07). Two sets of charts are constructed with usually recommended subgroup size of 5 [19]. First six months' data are used in phase I to construct trail control limits. To produce good results in practice, three sigma control limits were used so that the probability of type I error is kept at 0.0027 [1]. These control limits are used in Phase II to monitor process outcomes with second half six months' data. The implementation and analysis for all test stations are performed using same procedure. In this section, station WH05 is used to demonstrate the implementation with the proposed model.

4.1. Classical Shewhart control charts (\bar{x} chart and R chart)

In figure 2, 5 points and 1 point violate the rules in \bar{x} chart and R chart respectively. However, in actuality, the process is said in compliance to industry standard as all reading and its tolerance coincidentally falls within the acceptance limits with measurement uncertainty guard band as shown in figure 3. With this, the violated points are considered false alarm, except for the points circled in red are considered true signal where there is large shift (rule 1) and small sustained shift (rule 6) on July 2015. To solve the false alarm problem, operator may compensate the error through process adjustment or the control engineer will perform the retrospective analysis to construct a new control limits.

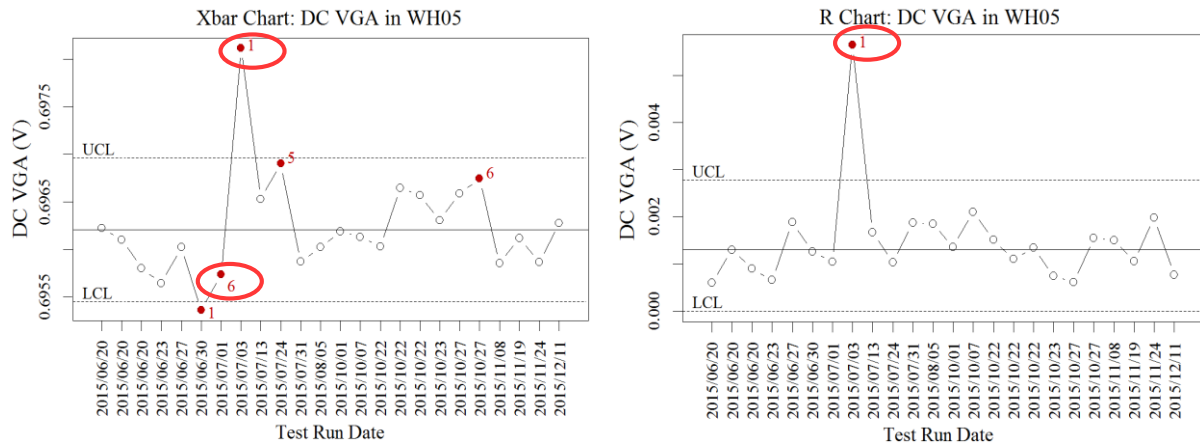
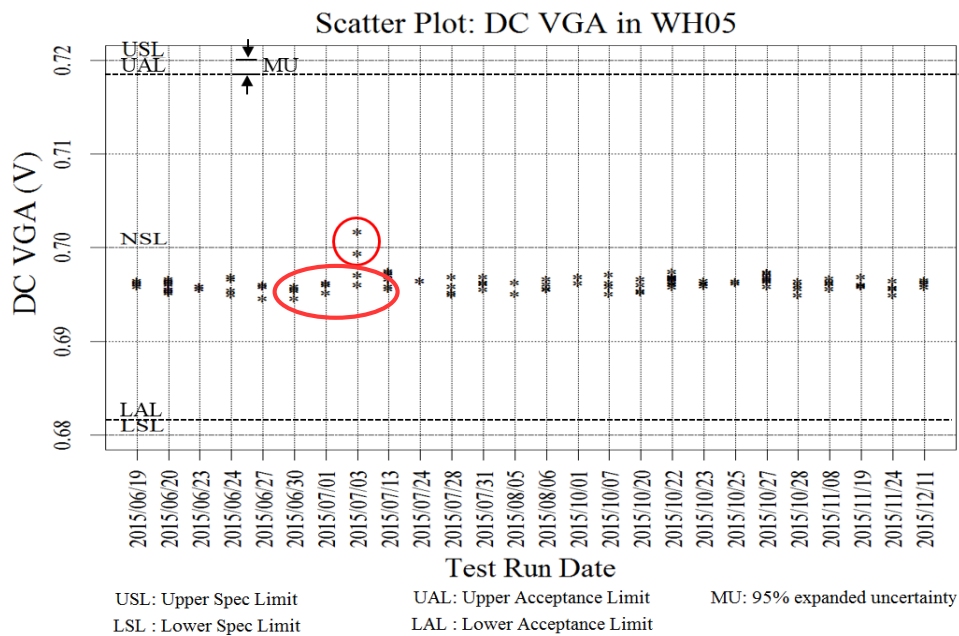
Figure 2. Shewhart \bar{x} chart and R chart for DC VGA test in station WH05

Figure 3. Scatter Plot for DC VGA test in station WH05

4.2. \bar{Z} chart and W chart with $\hat{\sigma}_{p_m}$ determined through through S -factor

First, measurement target (T) needs to be determined. DC VGA test is measured by comparing the voltage reading between oscilloscope (Scope) and digital multimeter (DMM). T_m value is calculated from repeated measurement for each station and recompiled in the event of DMM readjustment during the calibration or DMM replacement with another unit. Five input quantities (X_i) affecting the measurement result (Y) are identified, as shown in table 2. They undergo either Type A or Type B evaluation to obtain the standard uncertainties $u(x_i)$. X_1 is obtained from 15 repeated observations, the input estimates x_1 is evaluated using Type A. Other input quantities (X_2 to X_5) are the equipment specification and the resolution of the reported measured value, the input estimates x_2 to x_5 are evaluated using Type B with rectangular distribution.

The combined standard uncertainty $u_c(y)$ is computed from individual $u(x_i)$ using equation (10):

$$u_c(y) = \sqrt{[c_1 u(x_1)]^2 + [c_2 u(x_2)]^2 + [c_3 u(x_3)]^2 + [c_4 u(x_4)]^2 + [c_5 u(x_5)]^2}$$

$$u_c(y) = 0.638 \text{ mV}$$

The expanded uncertainty (U_m) is calculated with the coverage factor $k_m = 2$ and rounded to two significant figures.

$$U_m = 2u_c(y) = 1.3 \text{ mV}$$

Table 2. Evaluation of standard uncertainties

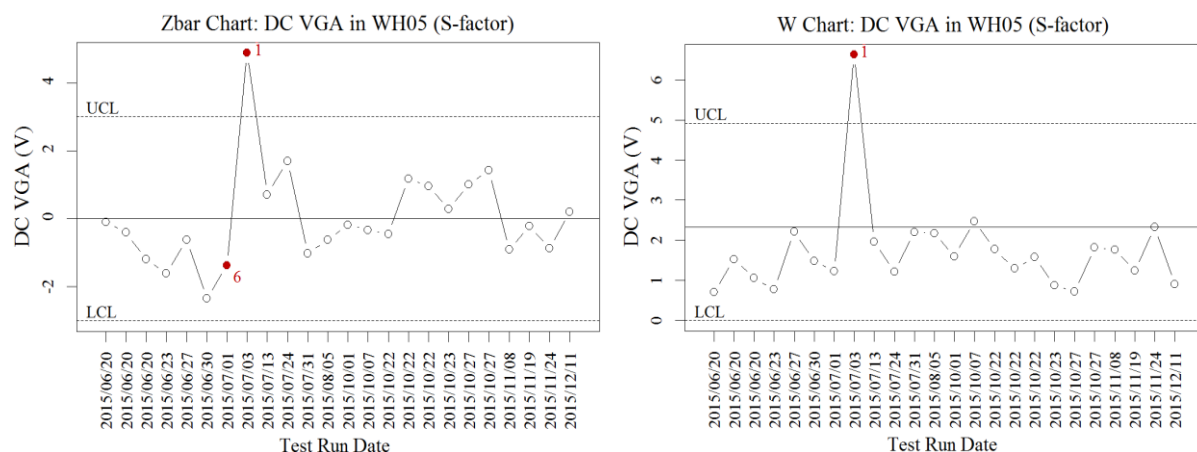
X_i	Contributors	Type	ν_i	\pm Limits	Units	Distribution	C_i	$u(x_i)$
X ₁	Repeatability tests	A	14	3.21E-04	mV	Sigma	1	3.21E-04
X ₂	Voltage accuracy from DMM	B	∞	3.15E-05	mV	Rectangular	1	1.82E-05
X ₃	Resolution error of DMM	B	∞	5.00E-03	mV	Rectangular	1	2.89E-03
X ₄	Vertical resolution error of Scope with input signal	B	∞	7.81E-01	mV	Rectangular	1	4.51E-01
X ₅	Vertical resolution error of Scope without input signal	B	∞	7.81E-01	mV	Rectangular	1	4.51E-01

With the estimated values of $\hat{\sigma}_{x_m}$ and $\hat{\sigma}_{u_m}$, the max $\hat{\sigma}_{p_m}$ is computed using Pythagoras's theorem in equation (16). S-factor (S_{f_m}) is calculated with a ratio between max $\hat{\sigma}_{p_m}$ and min $\hat{\sigma}_{p_m}$, as shown in table 3.

Table 3. Estimation of $\hat{\sigma}_{p_m}$ with S-factor

Station	U_m	$\hat{\sigma}_{x_m}$	$\hat{\sigma}_{x_u}$	Min $\hat{\sigma}_{p_m}$	Max $\hat{\sigma}_{p_m}$	S_{f_m}
WH05	1.30E-03	5.63E-04	6.50E-04	5.63E-04	8.60E-04	1.527
WH06	1.30E-03	5.61E-04	6.50E-04	5.61E-04	8.58E-04	1.531
WH07	1.30E-03	6.06E-04	6.50E-04	6.06E-04	8.89E-04	1.466

The transformation expression in equation (20) and equation (21) are applied to plot \bar{Z} chart and W chart respectively as shown in figure 4. The results showed that there were no false alarm points found and capable to detect the large shift from mean. As of now, the implementation is completed for station WH05; similar process will be repeated for other stations WH06 and WH07.

Figure 4. Modified \bar{Z} chart and W chart for DC VGA test in station WH05 with S-factor

5. Result and Discussion

The summarized results of the case study are recorded in table 4. At this case, the $U/k\sigma_x$ ratio is at 1.1, the measurement error marginally affects the process standard deviation. From the analysis results from Shewhart \bar{x} chart, all test stations had many points exceeding the control limits and some abnormal patterns are falsely detected. These false alarms caused many unnecessary process

adjustment and loss of confidence in SPC. With the S-factor approach, the analysis results showed that the model performed very well in both \bar{Z} chart and W chart with zero false alarms in all stations. The model reduced false alarms rate by up to 13% in comparison to the classical Shewhart \bar{x} chart. Based on the results of observations, all test stations are in normal and controlled behavior, except for station WH05 where the shift occurs in the process. In this case study, all methods were able to detect these assignable causes. Results of the case study proved that the model with S-factor is efficient and effective for T&M process.

Table 4. Summary result of the case study

Station	Chart Type	Est Std Dev Method	Total Points	False Detected in Nelson Rules Test								False Alarm		Assignable causes detected
				R1	R2	R3	R4	R5	R6	R7	R8	FA	FA%	
DC VGA WH05	\bar{x}	Shewhart	24	1	0	0	0	1	1	0	0	3	13%	2
	\bar{Z}	S-Factor	24	0	0	0	0	0	0	0	0	0	0%	2
	R	Shewhart	24	0	0	-	-	0	0	-	-	0	0%	1
	W	S-Factor	24	0	0	-	-	0	0	-	-	0	0%	1
DC VGA WH06	\bar{x}	Shewhart	26	1	0	0	0	0	0	0	0	1	4%	0
	\bar{Z}	S-Factor	26	0	0	0	0	0	0	0	0	0	0%	0
	R	Shewhart	26	0	0	-	-	0	0	-	-	0	0%	0
	W	S-Factor	26	0	0	-	-	0	0	-	-	0	0%	0
DC VGA WH07	\bar{x}	Shewhart	23	1	0	0	0	0	0	0	1	2	9%	0
	\bar{Z}	S-Factor	23	0	0	0	0	0	0	0	0	0	0%	0
	R	Shewhart	23	0	0	-	-	0	0	-	-	0	0%	0
	W	S-Factor	23	0	0	-	-	0	0	-	-	0	0%	0

6. Conclusions

This paper proposed a modified SPC model combining modified guard band and control charts (\bar{Z} chart and W chart) to address issues caused by short production runs and measurement errors. The model utilized the measurement target and measurement uncertainty to standardize the observed value. S-factor determines the estimation of the process standard deviation for control limits tolerance. The effectiveness of proposed model was demonstrated by a case study in real industry and it shows that the measurement error marginally affected the process standard deviation. The results revealed that the model significantly reduced false alarm rate compared to the one using classical Shewhart control charts. Moreover, the results proved that the model using the S-factor can rescale the process standard deviation in an efficient and effective manner. The proposed model using the modified control charts is practical for T&M manufacturing to eliminate false alarm, without sacrificing sensitivity to level shifts.

References

- [1] Montgomery D C 2013 *Statistical quality control: A modern introduction 7th ed.* (Singapore: John Wiley & Sons)
- [2] Bothe D R 1989 A powerful new control chart for job shops *43rd Annual Quality Congress Transactions May 1989 (Toronto)* (ASQC) pp 265-270
- [3] Costa A F B and Castagliola P 2011 Effect of measurement error and autocorrelation on the \bar{X} chart *Journal of Applied Statistics* **38**(4) 611-673
- [4] Barrera J 2012 Analysis of some statistics used in short runs charts *Proc. of 15th International Conference on Experimental Mechanics 22-27 July 2012 (Porto/Portugal)* (ICEM15) pp 1-2

- [5] Wheeler D 1991 Short Run SPC *SPC press*
- [6] Farnum N 1992 Control charts for short runs: nonconstant process and measurement error *Journal of Quality Technology* **24**(3) 138-144
- [7] Moore S S and Murphy E 2013 Process visualization in medical device manufacture: an adaptation of short run SPC techniques *Quality Engineering* **25**(3) 247-265
- [8] Del Castillo E, Grayson J M, Montgomery D C and Runger G C 1996 A review of statistical process control for short run manufacturing systems *Communications in Statistics - Theory and Methods* **25**(11) 2723-2737
- [9] Pou J M and Leblond L 2015 Control of customer and supplier risks by the guardband method *International Journal of Metrology and Quality Engineering* **6** 205
- [10] JCGM 100: 2008 *Evaluation of measurement data– Guide to the expression of uncertainty in measurement (GUM 1995 with minor corrections)* (Joint Committee for Guides in Metrology)
- [11] JCGM 200: 2012 *International Vocabulary of Metrology – Basic and General Concepts and Associated Terms (VIM 3rd ed.)* (Joint Committee for Guides in Metrology)
- [12] UKAS 2007 *The Expression of Uncertainty and Confidence in Measurement M3003 2nd ed.* (UK: United Kingdom Accreditation Service)
- [13] Taylor B N and Kuyatt C E 1994 *Guidelines for Evaluating and Expressing the Uncertainty of NIST Measurement Results* (MD: National Institute of Standards and Technology, USA)
- [14] Instone I 1996 Simplified method for assessing uncertainties in a commercial production environment *Teste and measurement Metrology Forum (London)* pp 1-7
- [15] Bell S 2001 *Measurement Good Practice Guide No 11 (Issue 2): A Beginner's Guide to Uncertainty of Measurement* (UK: National Physical Laboratory)
- [16] Nelson L S 1984 The Shewhart control chart-tests for special causes *Journal of Quality Technology* **16**(4) 237-239
- [17] Noskievicova D 2013 Complex control chart interpretation *International Journal of Engineering Business Management* **5** (13:2013) 1-7
- [18] Scrucca L 2004 qcc: An R package for quality control charting and statistical process control *R News* **4**(1) 11-17
- [19] Reynolds M R and Stoumbos Z G 2004 Should observations be grouped for effective process monitoring *Journal of Quality Technology* **36** 343-366