Performance analysis of different tuning rules for an isothermal CSTR using integrated EPC and SPC

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Abstract. This paper demonstrates the integration of Engineering Process Control (EPC) and Statistical Process Control (SPC) for the control of product concentration of an isothermal CSTR. The objectives of this study are to evaluate the performance of Ziegler-Nichols (Z-N), Direct Synthesis, (DS) and Internal Model Control (IMC) tuning methods and determine the most effective method for this process. The simulation model was obtained from past literature and re-constructed using SIMULINK MATLAB to evaluate the process response. Additionally, the process stability, capability and normality were analyzed using Process Capability Sixpack reports in Minitab. Based on the results, DS displays the best response for having the smallest rise time, settling time, overshoot, undershoot, Integral Time Absolute Error (ITAE) and Integral Square Error (ISE). Also, based on statistical analysis, DS yields as the best tuning method as it exhibits the highest process stability and capability.

1. Introduction

In today's competitive market, many manufacturing industries are seeking ways to optimize process performance and improve product quality in order to maintain a successful operation. For this, two methods are commonly practiced, namely Engineering Process Control (EPC) and Statistical Process Control (SPC) [1].

Variations are undoubtedly among the major concerns for every manufacturing industry. The concept of variation states that no two products will be perfectly identical even when extreme care is taken to ensure the products remain synonymous between one another [2]. Variations can be classified into two categories, namely common cause and special cause [3]. Common cause variation contributes to more than 80% of product defect due to equipment failure, gradual deterioration, wear and tear, irregular scheduled maintenance and many more. These variations are natural and is inherent within the process, which makes it difficult to be completely eliminated. On the other hand, about 20% of the defect is due to special cause variation such as improper tuning, incorrectly adjusted machinery and wrong choice of material [4].

1.1 Statistical Process Control

SPC is a well-known method used to achieve process stability through variability reduction [5]. This is accomplished by monitoring the process condition and detecting the presence of special cause variation. The main reason for the implementation of SPC is to obtain higher and steady product

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quality. The term quality varies from one aspect to another, which can be measured based on the level of performance, reliability, durability, serviceability and compliance to standards [6].

One of the primary tools used in SPC is the control charts, which was pioneered by an American physician, engineer and statistician named Walter A. Shewhart in the late 1920s [1]. The purpose of a control chart is to observe the inputs and outputs of a process and measure the parameters against a set of control limits, known as the lower control limit (LCL) and upper control limit (UCL). This is useful in detecting the presence of assignable cause variation and determining whether the process is in-control or out-of-control. Whenever an abnormality is detected, SPC will transmit a signal to the operator whom will carry out investigation and find solutions to rectify the situation. Besides control charts, several other tools available in SPC, which are collectively known as the Seven Quality Tools.

For years, SPC has been successfully implemented within the chemical and process industries as a tool to monitor and maintain the consistency of process systems. The warmth and wide acceptance of SPC is complimented with various publications exploring its use in processes such as chlorine production [5], alkyd polymerization [7], paper and pulp production [8] and many others.

1.2 Engineering Process Control
EPC, or also known as automatic process control (APC) is another technique used to reduce variation and ensure the process output remains at a desired set point. This is accomplished through the use controllers, which perform continuous adjustments to the process variables in order to compensate the effect of disturbance [9].

Controllers play an important role in the implementation of EPC. Various types of controller are available such as PID, fuzzy logic, ANN and others. However, PID is still the most widely used controller in the manufacturing industry due to its advantages such as simple design, cost effective and produce satisfactory control performance [10]. The notations P, I and D are representative of its variables, which are process gain (K_c), time integral (τ_I) and derivative time (τ_D), respectively. Each variable is responsible in governing the stability and response of the process [11]. There are different ways to which a PID controller can be configured into, such as feedback, feedforward and feedback-feedforward, although the former provides the simplest control system.

1.3 Integration of EPC and SPC
Generally, both methods seek to reduce variation as their main objective, albeit in different ways. SPC tracks the process parameters and signals for the presence of assignable cause variation. EPC on the other hand maintains the process output at a specified target by minimizing the effect of disturbance. These are sometimes viewed as a disadvantage as SPC is not able to automatically eliminate the source of variation meanwhile EPC does not address the root cause.

The integration of EPC and SPC initially began in 1988 when Box and Kramer proposed the concept to the SPC research community [9]. Over time, the approach gained momentum and attracted the attention of many researchers as results showed that the use of integrated EPC/SPC yields superior performance compared to the use of either alone. Hence, recent studies have shown increasing interest towards developing an integrated EPC/SPC system to achieve better process performance and product quality.

Within the field of Chemical Engineering, reactors are looked upon as the "heart" of every chemical process. CSTR is among the types of reactors that are frequently used in manufacturing industries as it is simple to construct, operates at low cost and applicable for all types of fluids. However, due to its complex and non-linear characteristics, control of product concentration is difficult and often requires an accurate model [12]. This paper serves to study the integration of EPC and SPC for the control of product concentration for an isothermal CSTR through the following objectives: 1) Analyse the process performance using different tuning method and 2) Determine the most effective type of tuning method by comparing the process stability and capability.

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Unfortunately, there has been little effort given to implement an integrated EPC/SPC system for a CSTR. Hence, it is with hope that this study would provide useful information as well as exposure for future researchers to carry out improved trials and discover new findings within this field of study.

2. Methodology

This study was conducted in two stages, namely, process simulation and statistical analysis. Firstly, the process was modelled using SIMULINK MATLAB R2015a as demonstrated by [13] in Figure 1 and Figure 2. The isothermal CSTR has following reaction kinetics, which is known as Van de Vusse reaction:

$$A \xrightarrow{k_1} B \xrightarrow{k_2} C$$
$$2A \xrightarrow{k_3} D$$

Table 1: Parameters for Van de Vusse reaction.

Parameter	Value
k_1	0.83 min^{-1}
k_2	1.66 min^{-1}
k_3	0.166 mol^{-1} min^{-1}
Steady state feed concentration, C_A	10 $gmol^{-1}$

The controller variables (K_c, τ_I and τ_D) were calculated using DS and IMC tuning methods whereas the variables for Z-N method was obtained from [13]. Each process response was evaluated based on the rise time, settling time, overshoot, undershoot, Integral Time Absolute Error (ITAE) and Integral Square Error (ISE). Next, the data from the process output were transferred to Minitab 17 where Process Capability Sixpack was used to analyze the process stability, capability and normality. The number of samples used for this analysis was 125, which is outlined by the Acceptance Quality Limit (AQL).

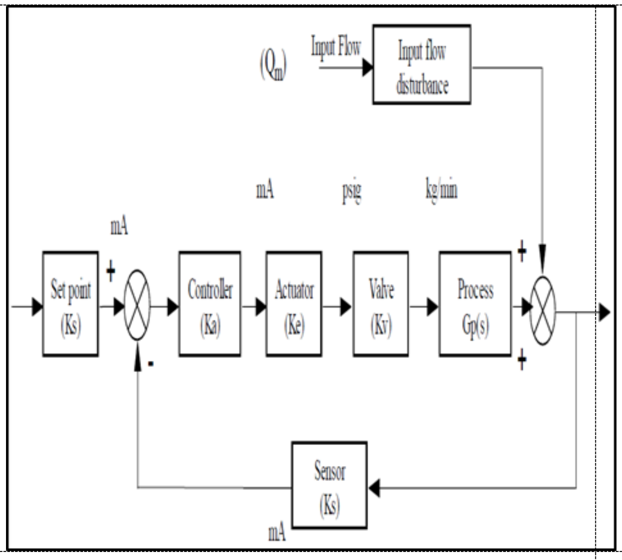

Figure 1. Block diagram based feedback control for product concentration control of isothermal CSTR [13].

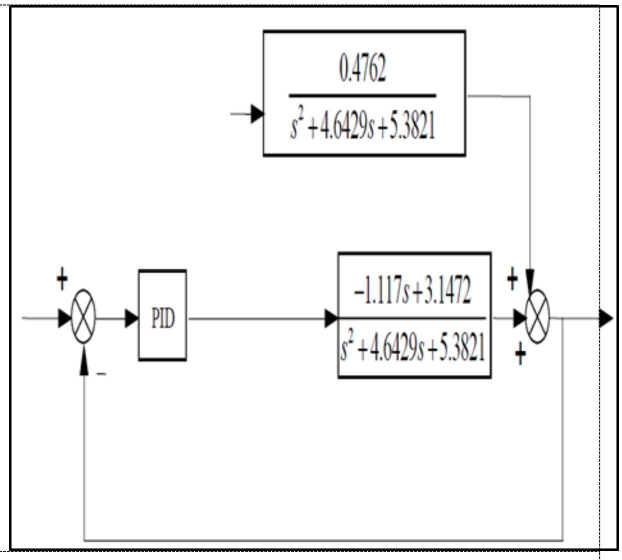

Figure 2. Transfer function based feedback control for control of product concentration of isothermal CSTR [13].

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2.1 Ziegler Nichols
According to [10], Z-N is the most widely used method to determine the variables of a PID controller. The principle technique for PID controller tuning are step response and ultimate frequency. The unit step response method is based on the open-loop response of the system and is characterized by two parameters, namely delay (L_1) and time constant (τ). These two parameters can be obtained by drawing a tangent at the point of inflexion, where the slope of the step response is at its maximum. The intersection between the tangent and coordinate axes produce the process parameters, which are then used to calculate the controller variables. The values of K_c, τ_I, and τ_D are 0.2, 0.95 and 0.23, respectively.

2.2 Direct Synthesis
According to [10], DS method for PID controllers are usually based on a time-domain or frequency-domain performance criterion. The controller is designed based on a closed-loop transfer function which is then used to perform analytical calculation and ensure the set point of the closed-loop matches the desired response. One of the advantages of using the DS approach is that performance requirements are directly integrated through specification of the closed-loop transfer function. Also, it is able to provide valuable information between the relationship of the process model and the controller [14]. The calculated values of K_c, τ_I, and τ_D are 0.6880, 1.1501 and 0.5448, respectively.

2.3 Internal Model Control
IMC method has been gaining increasing popularity in controller implementations, although PID controllers are still the standard type of controller used for this method. According to [10], the objective of IMC method is to achieve a fast and accurate set point tracking by removing the effect of disturbance as effectively as possible and also ensuring insensitivity to modelling error. An advantage of IMC method is that it allows uncertainty and trade-offs between performance and robustness to be considered in a systematic approach [14]. The calculated values of K_c, τ_I, and τ_D are 0.2755, 0.8627 and 0.2154, respectively.

2.4 Minitab
Minitab is a software that is widely used within the academic, business and government sectors for its wide collection of statistical tools. [15]. For this study, Minitab is used to produce a report called Process Capability Sixpack. It is consisted of control charts, histogram, normal probability plot and process capability chart. For this study, 125 sample data from the process output were used to produce the Process Capability Sixpack to analyse the stability, normality and capability of each tuning method.

3. Results and Discussion

3.1 Assumptions
Several assumptions were made throughout this study in order to achieve the objectives. Amongst them are:

- Desired product concentration (set point) is equal to the feed concentration at 10 $gmol^{-1}$.
- Flowrate disturbance is represented with "random numbers" in SIMULINK MATLAB.
- Upper Specification Limit (USL) and Lower Specification Limit (LSL) of the process is assumed to be 10.00±0.05 $gmol^{-1}$.
- The significance level (α) for normality test is 1%.

3.2 Process without Control Scheme
Before analyzing the effectiveness between Z-N, DS and IMC, the process was firstly modelled without a control scheme as seen in Figure 3. The purpose of this setup is to observe the output when no corrective action is available to minimize the effect of disturbance. Based on Figure 4, it is

observed that the process is unable to reach the desired set point of 10 gmol^{-1}, but instead only managed to achieve 5.85 gmol^{-1}. Also, the response displays a large undershoot at the initial stage of the process. From these observations, it is clear that a control scheme is indeed required obtain a desirable and satisfactory process response.

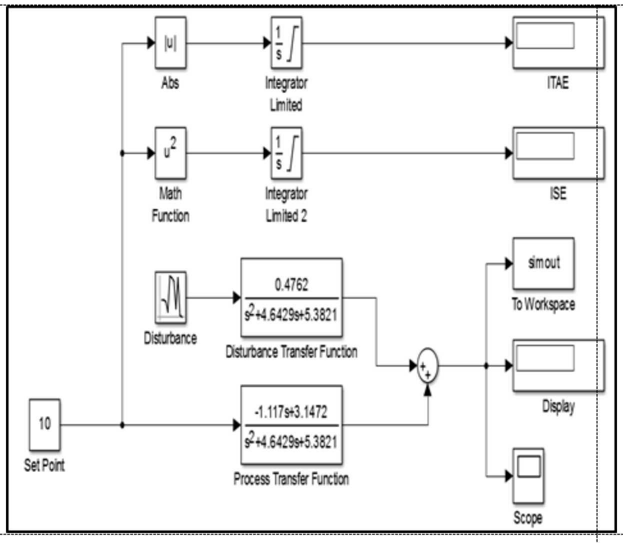

Figure 3. Process model without control scheme.

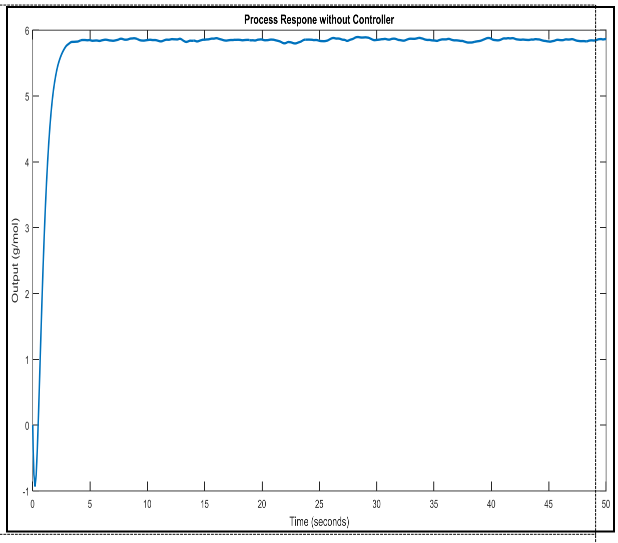

Figure 4. Process response without control scheme.

3.3 Comparison between Z-N, DS and IMC

In this section, comparison will be made for each of the process response obtained from Z-N, DS and IMC methods. The criteria used to evaluate the effectiveness of each tuning method are rise time, (τ_R), settling time (τ_S), overshoot, undershoot, integral square error (ISE) and integral time absolute error (ITAE). The process was modelled as seen in Figure 5 and the response produced from each method are shown in Figure 6.

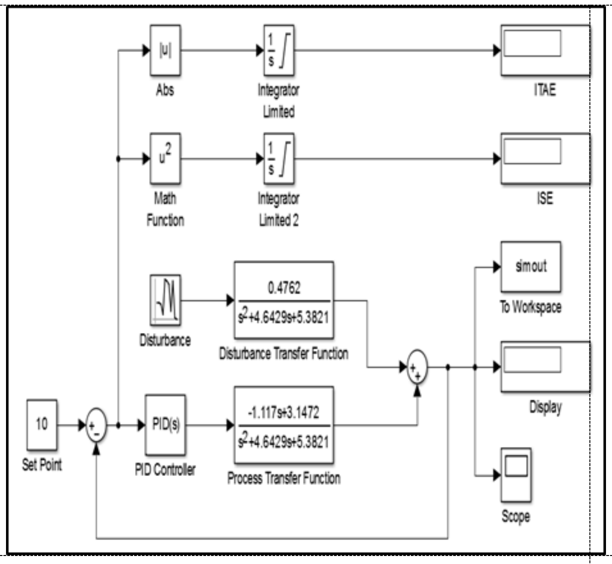

Figure 5. Process model with PID controller.

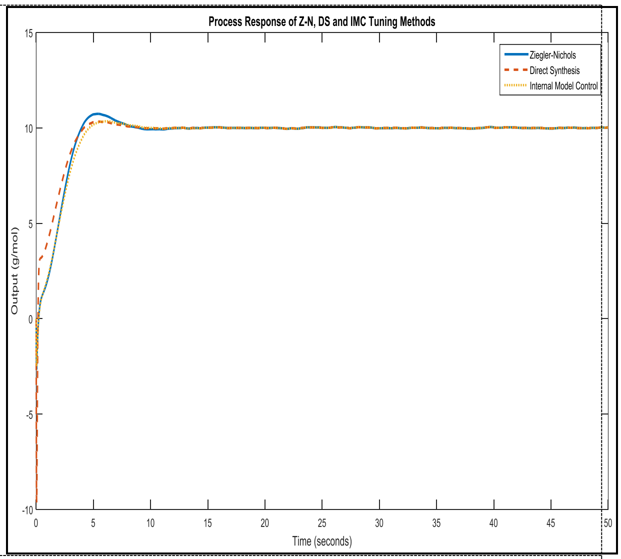

Figure 6. Process response for Z-N, DS and IMC methods.

Based on Figure 6, it is observed that DS method produces the best process response as it has smallest τ_R and τ_S as well as lowest ITAE and ISE. However, it also displays the highest undershoot when compared to other tuning methods. The second-best response is produced from Z-N and lastly, IMC method. Table 2 presents a result summary for each tuning method.

Table 2. Results summary for Z-N, DS and IMC methods.

Method	Rise time (s)	Settling time (s)	Overshoot (%)	Undershoot (%)	ITAE	ISE	Rating
Ziegler-Nichols	0.19	9.23	7.94	28.57	18.64	127	Moderate
Direct Synthesis	0.038	9.04	7.06	96.08	15.62	114.3	Best
Internal Model Control	0.038	10.77	4.03	25.28	22.34	145.4	Worst

3.4 Fine Tuning

A common approach that is practiced in EPC in order to achieve better process response is by performing fine tuning to the controller variables. This is done by adjusting K_c, τ_I, and τ_D through trial-and-error until a satisfactory response is produced. The new controller variables are presented in Table 3 meanwhile Figure 7 presents the process response after fine tuning was performed.

Table 3. Controller variables for Z-N, DS and IMC methods after fine tuning.

Tuning method	K_c	τ_I	τ_D
Ziegler-Nichols	0.6	0.95	0.0144
Direct Synthesis	0.6880	1.15	0.0334
Internal Model Control	0.5510	0.8627	0.0135

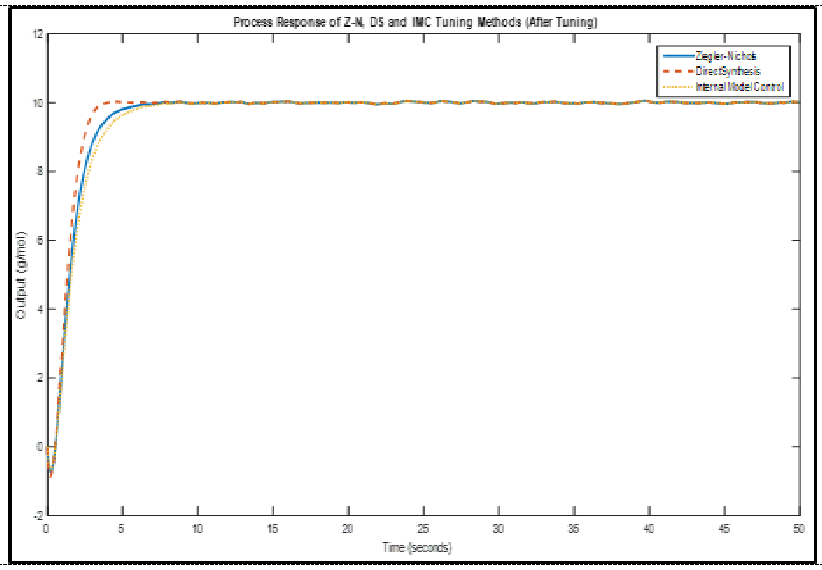

Figure 7. Process response for Z-N, DS and IMC methods after fine tuning.

Based on Figure 7, it can be observed that the process response had improved significantly. The most noticeable difference is that the overshoot was eliminated completely and the undershoot was minimized. Apart from that, the values of ISE and ITAE were also reduced, which indicate that the error within the process was reduced. However, τ_r increased slightly after performing this step, meaning that the process will take a longer time to reach the set point. Apart from that, τ_r decreased which means the process will take a shorter time to stabilize at the set point. Table 4 presents the result summary for each of the tuning method after performing fine tuning.

Table 4. Results summary for Z-N, DS and IMC methods after fine tuning.

Method	Rise time (s)	Settling time (s)	Overshoot (%)	Undershoot (%)	ITAE	ISE	Rating
Ziegler-Nichols	0.38	7.50	-	7.04	18.04	127	Moderate
Direct Synthesis	0.19	5.00	-	8.94	15.62	114.3	Best
Internal Model Control	0.38	8.77	-	7.88	20.42	134.8	Worst

3.5 Performance Tests

Once the optimum controller variables have been calculated, a series of performance tests were conducted to measure its performance in handling changes in set point and disturbance load [11]. To perform set point test, the process was simulated two (2) times, each with different set points – 15 and 20 $gmol^{-1}$. Meanwhile for disturbance test, the process response was studied under two conditions, firstly without disturbance and then with the presence of disturbance.

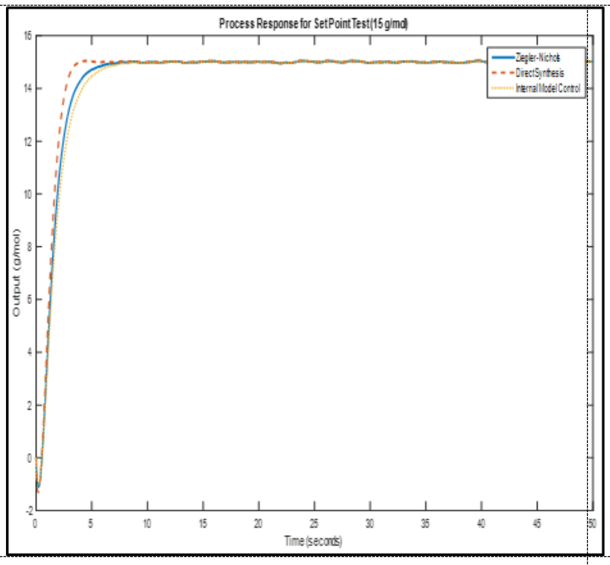

Figure 8. Set point test for 15 $gmol^{-1}$.

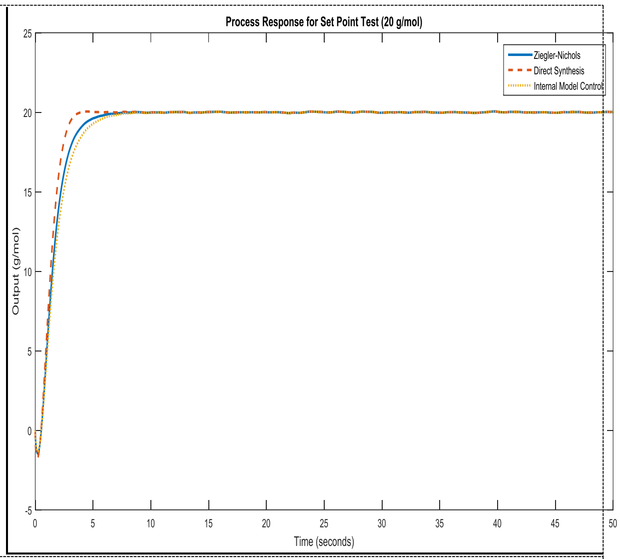

Figure 9. Set point test for 20 $gmol^{-1}$.

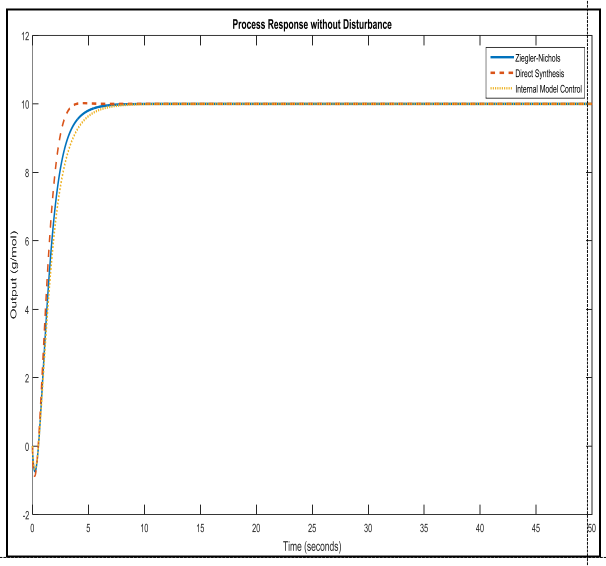

Figure 10. Process response without disturbance.

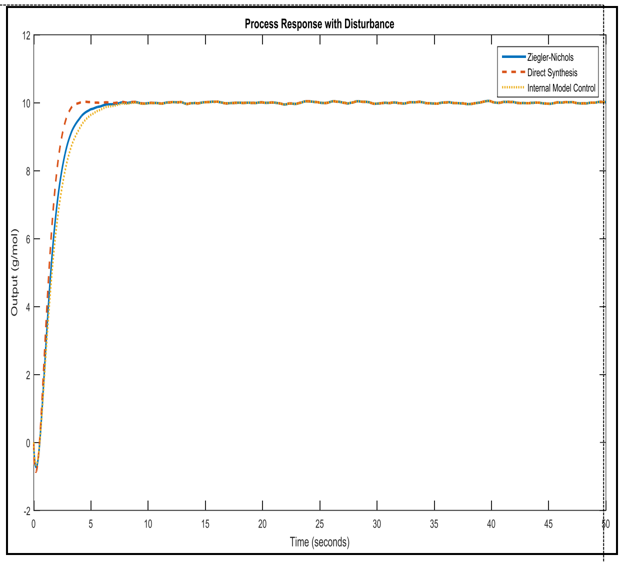

Figure 11. Process response with disturbance.

The results of the set points tests are as shown in Figure 8 and Figure 9. It is observed that the process manages to reach each of the specified target with minimum disturbance. Hence, it is proven that the controller variables used in table 3 pass the set point tests and can be applied for varying set points.

The results of disturbance test are presented in Figure 10 and Figure 11. Based on these graphs, it is seen that the response produced without disturbance is slightly more stable compared to when disturbance is present. However, the latter still manages to achieve the targeted specification of 10 $gmol^{-1}$ with minimal fluctuation. It should be worth considering that a response such as in Figure 10 is unlikely to occur in industrial practice as various disturbance loads will affect the process variables.

3.6 Process Capability Sixpack

Up until this point, the results shown represent the principles of EPC. However as stated by [16], the control of process variables would be significantly improved when SPC is used simultaneously with EPC. Hence, a Process Capability Sixpack will be used to measure the performance of the process with regards to its stability, normality and capability.

3.6.1 Ziegler-Nichols Method

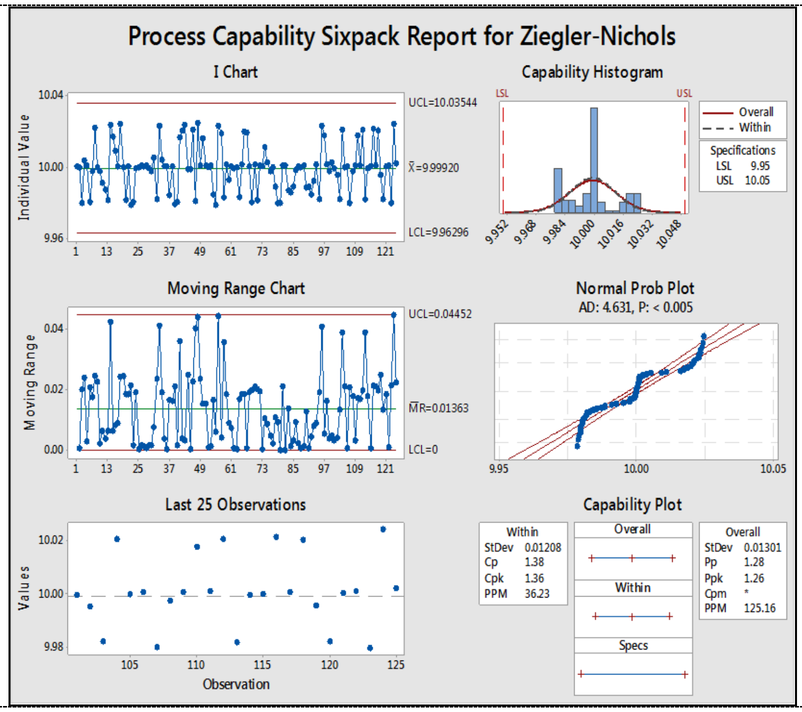

Figure 12. Process Capability Sixpack for Z-N method.

The Process Capability Sixpack report in Figure 12 shows the control charts for I and MR. These charts are used to monitor the presence of special cause variation which is the frequent cause of product defect. It is observed that all of the points lie within the UCL and LCL, indicating that the process is stable and in-control. The average product concentration obtained from the sample is 10.00 $gmol^{-1}$, which is the exact desired specification.

A capability histogram is also included to display the process spread relative to the specification limits. As mentioned previously, the USL and LSL are assumed to be 10.00±0.05 $gmol^{-1}$, which calculates into 10.05 and 9.95, respectively. Based on the chart, it is observed that all of the data fall within the specification limits, suggesting that the process is capable. Additionally, the process spread lies at the center of the specification limits, implying that the process has a high tendency of forming a product that is closest to the average concentration.

The capability of the process can be further analyzed using the process capability plot. Here, various performance indices are provided such as C_p, C_{pk}, P_p and P_{pk}. However, only the value of C_{pk} will be used to measure the process capability as C_p does not consider the location of the process spread (relative to the center of the specification limits) meanwhile P_p and P_{pk} is only applicable when the process is out-of-control [17]. According to [18] the general acceptable value of C_{pk} is 1.33 and any lower than that means the variation is either too wide compared to the specifications or that the process is off-centered. Based on the capability plot, the C_{pk} obtained is 1.36, which is above the acceptable value. This further proves that the process is capable and can indeed achieve the desired specification.

Besides that, a normal probability plot is included to determine the normality of the process. This graph is used to determine whether the data is normally distributed or otherwise. Before conducting the analysis, several parameters need to be clearly understood such as the significance level (α), *p*-value and null hypothesis (H_0). As a brief summary, the null hypothesis is either to be accepted or rejected depending if the *p*-value is greater or lesser than α, respectively.

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For this study, the α is assumed to be 1% or 0.01. However, the *p*-value obtained from the graph is <0.005, which is lesser than 0.01. This means that the null hypothesis is rejected and that the data is not normally distributed.

3.6.2 Direct Synthesis Method

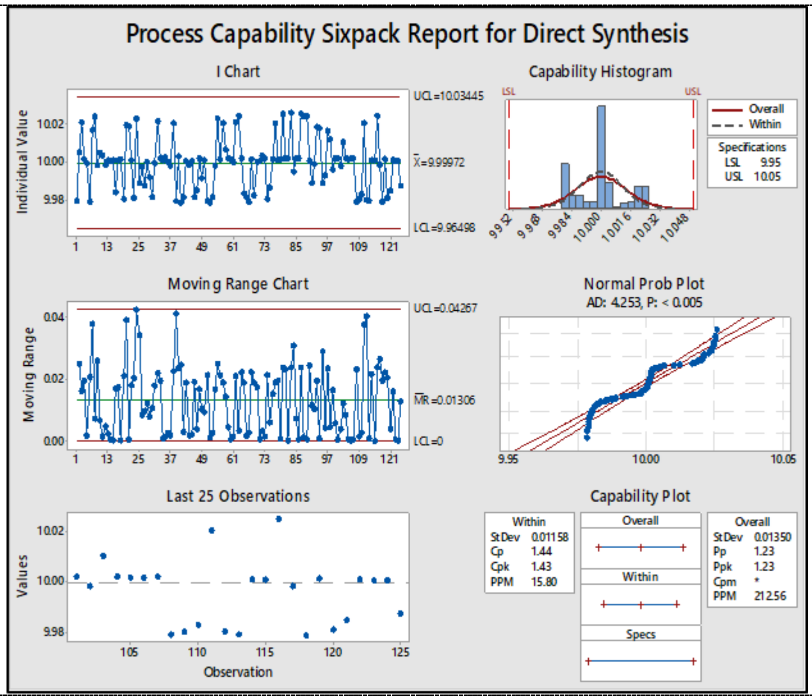

Figure 13. Process Capability Sixpack for DS method.

Figure 13 shows the Process Capability Sixpack for DS method. Based on the I-MR charts, it is observed that all of the points lie within the specification limits, implying that special cause variation is absent from the process and that the process is stable. Similar to Z-N method, the average concentration of the sample is 10.00 $gmol^{-1}$, which means that the product achieves the desired specification.

Besides that, the histogram shows that the process spread is well-centered between the USL and LSL. This indicates that the process has a high tendency of producing a product that is nearest to the average concentration. Based on the capability plot, the C_{pk} obtained is 1.43, which proves that the process is capable. The C_{pk} obtained from DS method is greater compared to Z-N, meaning DS method is more capable compared to Z-N.

By observing the normal probability plot, it shows that the *p*-value is < 0.005, which is lesser than 0.01. This means that the null hypothesis is rejected and the sample data is not normally distributed.

3.6.3 Internal Model Control Method

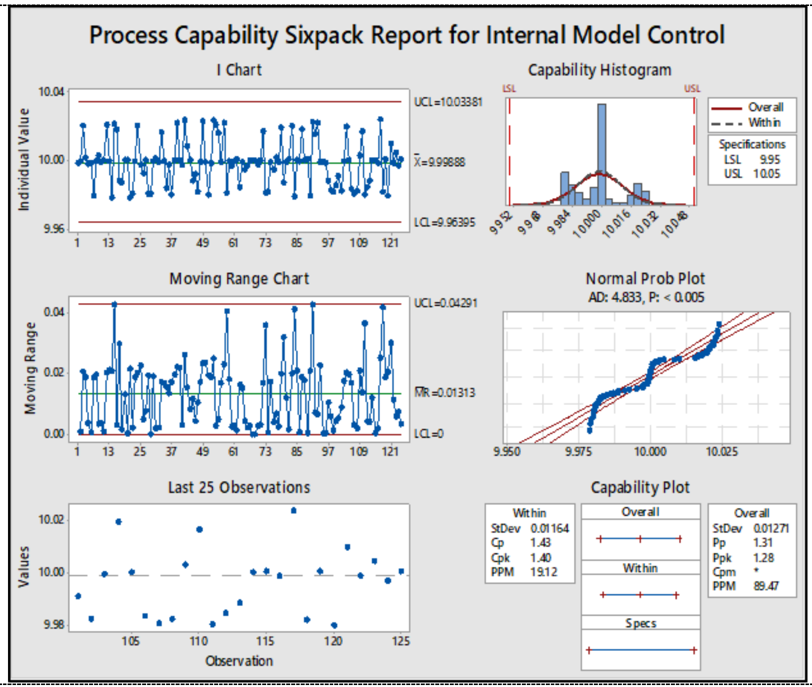

Figure 14. Process Capability Sixpack for IMC method.

The final tuning method that will be analyzed is the IMC as shown in Figure 14. Based on the I-MR charts, all of the points lie within the UCL and LCL, similar to the other two methods. This shows that the process does not contain special cause variation and that it is in-control.

The capability histogram shows that the process spread lie well within the LSL and USL, implying that the process is capable. Similar to Z-N and DS method, the process spread is located at the middle of the specification limits, indicating that the product formed has a high tendency of having the desired concentration.

By referring to the capability plot, the C_{pk} obtained is 1.40, which is greater than 1.33. This further supports the statement that the process is capable and is able to meet the desired specification. When comparing the C_{pk} values obtained from all of the tuning methods, Z-N produces the lowest value, followed by IMC and lastly, DS method.

The normal probability plot shows a p-value of <0.005, which is lesser than 0.01. This goes to show that the null hypothesis is rejected and that the data used is not normally distributed.

4. Conclusion

In this paper, control of product concentration for an isothermal CSTR was studied using different PID tuning methods. The tuning methods used were Ziegler-Nichols (Z-N), Direct Synthesis (DS) and Internal Model Control (IMC) as these are among the most commonly used tuning methods within the chemical and process industries. The simulation model was obtained from past literature and was re-constructed using SIMULINK MATLAB. Based on the results, DS produces the best process performance as it displays the shortest rise time and settling time, smallest overshoot as well as lowest ITAE and ISE. This is followed by Z-N method and lastly, IMC method. The process outputs were then used to study the stability, normality and capability of the process using Process Capability Sixpack in Minitab. Based on the results obtained, DS displays the best process performance for having the biggest C_{pk}, indicating that it is the most capable method that can achieve the desired specification. In conclusion, all of the tuning methods used in this study were proven to be able to control the product concentration for an isothermal CSTR, although DS yields as the best tuning method compared to the others. For recommendations, this study can be further expanded and improved upon by applying different tuning methods such as Cohen-Coon, Takahashi, and Lambda tuning methods to obtain a wider scope of result and comparison. Also, other SPC tools such as X-MR chart, EWMA, CUSUM and Hotelling T^2 may serve as an alternative for the statistical analysis.

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