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Applying DOE in Performance Optimization of an Automated Position Control System – A collaborated case study between two engineering technology courses

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Abstract

Hydraulic systems are widely used in industry, since they can produce large torques, high-speed responses with fast motions and speed reversals. Automatic control of hydraulic systems has evolved into an increasingly superior alternative for many industrial applications [1]. Advances in hydraulic hardware and electronics have combined to make the design and implementation of these systems more intuitive, reliable, cost effective, repeatable and user friendly. Controlling the position of a cylinder is one of the most demanding hydraulic motion control applications [2]. In a closed-loop position control system, the system performance is determined by various factors such as controller settings, system pressure, environment temperature, etc. In order to optimize the system performance, this study conducted utilizing Design of Experiment (DOE) on an automated hydraulic position control system. In the designed experiment, four controllable factors are considered at two different levels – three controller settings and the system pressure. The controller setting parameters include the proportional gain (P), the integral gain (I), and the derivative gain (D). These are the critical parameters for typical PID-based control systems [3]. The system performance is measured in step response time and the position accuracy. The step response time measures how fast the control system can response to a position error, and the position accuracy measures how accurate the system is in terms of position control. The statistical analysis, including Analysis of Variance and factorial plots, was carried out using a statistical software. The paper will illustrate the physical control system in hardware setup and software programming, the DOE method applied, data collection, and the statistical analysis. The results and future study will be explained and discussed.

Keywords: Design of Experiment (DOE), electrohydraulic system, closed-loop control, PID control, performance optimization

Introduction

This paper introduces a case study project collaborated between a Quality Management course and a Hydraulics course in a program of Engineering Technology and Management. The case study project demonstrated the implementation of a quality management methodology, Design of Experiments, in optimizing the performance of a real-world application.

Automatic control of hydraulic systems has evolved into an increasingly superior alternative for many industrial applications. Controlling the position of a hydraulic cylinder is one of the most demanding motion control applications. In this study, an automated hydraulic position control system is designed to control the linear motion position of a hydraulic cylinder through a touch screen HMI (Human-Machine Interface). The major components of the system include a Parker 3L hydraulic cylinder, a position sensor, a DF Plus electrohydraulic servo valve, a PID controller, a touch screen HMI display, and a H-Pack hydraulic power supply. The control method applied is a classic PID (proportional, integral, and derivative) control.

In a typical closed-loop position control system like this, the system performance is determined by various factors such as controller settings, system pressure, environment temperature, etc. In order to optimize the system performance, this study conducted a Design of Experiment (DOE) analysis on an automated hydraulic position control system. In the designed experiment, four controllable factors are considered at two different levels – three controller settings and the system pressure. The controller setting parameters include the proportional gain (P), the integral gain (I), and the derivative gain (D). These are the critical parameters for typical PID-based control systems. The system performance is measured in step response time and the position accuracy. The step response time measures how fast the control system can response to a position error, and the position accuracy measures how accurate the system is in terms of position control.

Statistical analysis using ANOVA was used on the data collected from to the designed experiment. The paper illustrates the physical control system in hardware setup and software programming, the DOE method applied, data collection, and the statistical analysis. The results and future study will be explained and discussed.

System Overview

The Electrohydraulic position control system consists of a hydraulic cylinder, a proportional valve, a position sensor, a fluid PID controller, and a HMI touch screen. The specifications of these major hardware components are listed in Table 1 below.

Table 1. List of hardware components

Part Name	Component Type	Part Number
Parker Fluid PID Controller	PID controller	
DF Plus Valve	Proportional directional control valve	D1FPE50FB9NB00 20
Parker 3L Cylinder	Hydraulic cylinder	01.50 F3LLUS23A 12.000
Parker H-Pak	Hydraulic power supply	H1B2 7T10P0X13909/13
Parker HMI	HMI display	XPR06VT-2P3

The layout of the system with major components is shown below in Figure 1.

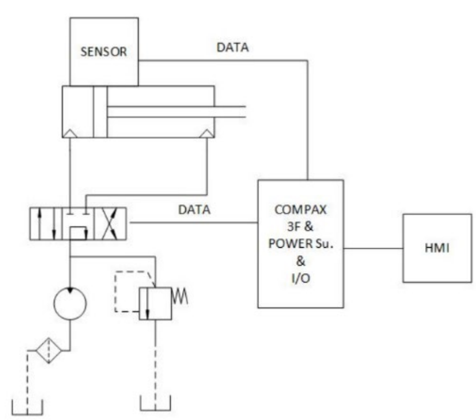

Figure 1: System layout with major components

The controller is programmed in CODESYS software and a PID control method is implemented [4]. The DF Plus Valve from Parker is used as the proportional directional control valve for this system. The proportional directional control valve controls the position of the cylinder based on DC signals ranging from -10v to +10v. A linear variable differential transformer (LVDT) provides position feedback to validate the cylinder position for improved accuracy and repeatability. The LVDT generates a feedback voltage proportional to the position change of the cylinder. The feedback voltage is then used by the controller to determine the control variable of the system. A picture of the whole system physical setup is shown in Figure 2 as below.

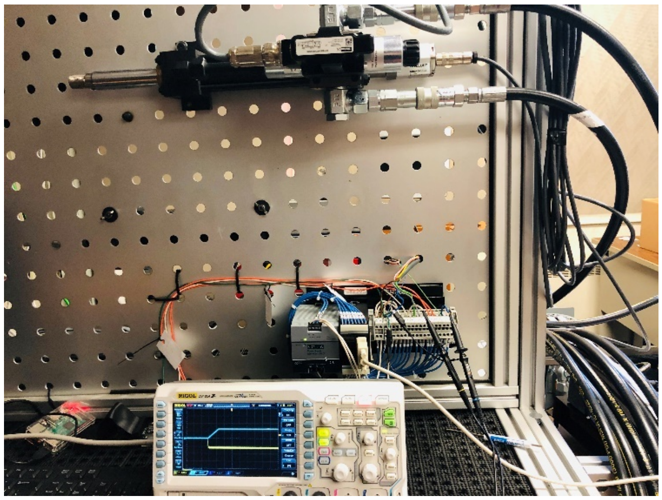

Figure 2: Picture of the system physical setup

System HMI Interface

A HMI interface is developed to provide a control panel to the position control system. The interface is programmed in Interact Xpress software, the layout of the control is designed as shown in Figure 3 below.

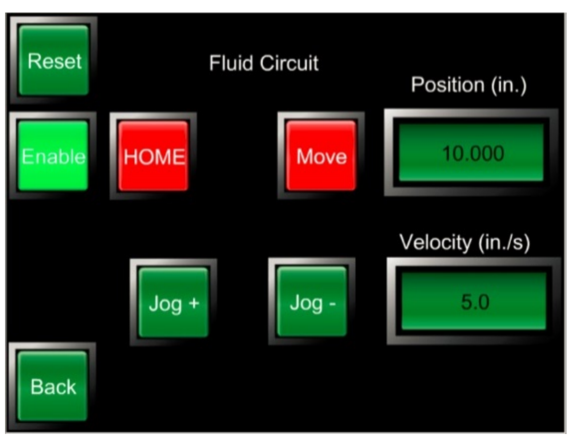

Figure 3: Position control panel

The control panel contains seven buttons and two variable input boxes. The Enable and Reset buttons are Boolean buttons to enable the valve drive and reset the input variables for position and velocity controls respectively. The Home button brings the cylinder piston to the pre-configured home position, and the Move button enables the motion control according to the input variables. Two Jog buttons (Jog+, Jog-) are used to allow manual jogging of the cylinder piston on both directions. There are variable input boxes to set position and velocity values for the motion control. Also a Back button is included to navigate back to the previous window. The interaction between this HMI interface and the application in Parker Servo Manager software is based on data tags created in Interact Xpress and the connection between the data tags and variables used in CODESYS program.

Literature Review

According to W. Edwards Deming, prediction requires theory and builds knowledge through systematic revisions based on comparison of prediction with observation [5]. For example, demonstrating a competency in an engineering lab requires instructions or a procedure. Based on the procedure, we predict a certain outcome when procedural steps are performed as prescribed. The outcome of the demonstration (observation) is compared to prediction (expectation). A noticeable difference between observation and expectation may require revision of the procedure (theory) then applying it again in order to gain knowledge.

A robust methodology for acquiring knowledge is the Deming Cycle of Plan-Do-Study-Act or PDSA. Deming refers to it as the Shewhart Cycle [6]. Figure 4 shows that the PDSA cycle is continuous and thus guarantees the temporal dimension for the theory of knowledge. In other words, knowledge is gained after each cycle and future cycles are undertaken with accumulated knowledge. Such knowledge can be gained through experimentation. The purpose of experimentation is to gain the knowledge about reducing and controlling variation in the process or the product by determining which process factor(s) significantly impact the outcome [7].

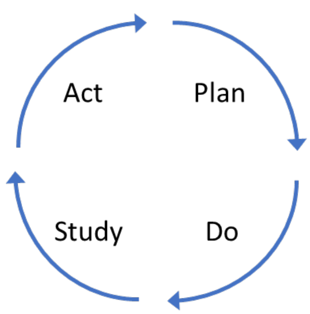

Figure 4: Plan-Do-Study-Act (PDSA) Cycle

For experiments to be run and analyzed efficiently, a scientific approach in planning must be followed [D]. While one-factor-at-a-time is extensively used in experimentation, design of experiment (DoE) methods, particularly factorial design, have advantages over the one-factor-at-a-time method. These advantages include, but not limited to, the ability to estimate interactions and utilize fractional factorial. In DoE methodology, the process allows for appropriate data to be collected and analyzed using graphical and statistical methods for objective and valid conclusions [8]. Table 1 shows the phases of the PDSA cycle along with what each phase involves when using the DoE methodology

Table 2: PDSA Details

Phase	Description
Plan (P)	• Identify controllable factors affecting performance • Identify performance (response) variables • Design the experiment (e.g. factorial or fractional factorial design)
Do (D)	• Run the experiment • Collect data
Study (S)	• Analyze data graphically and statistically. • Use earlier analysis to build a temporal picture.
Act (A)	• What was learned and what changes are needed? • Are there issues with the learning process? • If another PDSA cycle is needed, go back to Plan (P)

DOE Design for System Optimization

In a closed-loop position control system, system performance normally can be analyzed based on the step response time (rise time), the steady-state error, and the peak overshoot. Due to the limitation of time and equipment, the step response time is selected as the parameter to be collected and analyzed in this project. The step response time is defined as the time the system responses to a step input signal from 10% to 90% of the steady state response. The steady-state error describes the accuracy of position regarding to target position. In this study, the step response time and position accuracy are measured and analyzed to by applying a DOE method.

In this study, four controllable factors are selected: the proportional gain (P), the integral gain (I), the derivative gain (D) of the controller setting, and the system pressure. The P, I, and D gains play critical roles in the controller's control behavior. For example, P gain is the proportional gain of the PID controller. Increasing the proportional gain will increase the amount of current to the valve proportional to the amount of error the system produces. Therefore, the response time to the step signals should decrease. However, increasing the P gain further will cause the valve current to quadruple which may result in oscillatory performance, and the valve could be damaged.

With four controllable factors to consider at two levels each (2^4), a full factorial design was generated and displayed in Table 3 below. This factorial design will allow us to investigate the main effects (as well as their two-way interactions should there exist any. This factorial design has 16 experimental combinations (runs).

Table 3: Experimental Design

ID	**Factor 1**	**Factor 2**	**Factor 3**	**Factor 4**
1	-1	-1	-1	-1
2	-1	-1	-1	1
3	-1	-1	1	-1
4	-1	-1	1	1
5	-1	1	-1	-1
6	-1	1	-1	1
7	-1	1	1	-1
8	-1	1	1	1
9	1	-1	-1	-1
10	1	-1	-1	1
11	1	-1	1	-1
12	1	-1	1	1
13	1	1	-1	-1
14	1	1	-1	1
15	1	1	1	-1
16	1	1	1	1

One of the constraints for running design of experiments in real life situations is the amount of time it takes to run the whole experiment. It is important to minimize the time it takes so that the total research and development time is reduced. This becomes more urgent if the process is already in production and needs to be taken out for running the experiment. It was determined that changing the *Pressure* setting from low to high or vice versa would take the longest of any factor setting changes. Therefore, *Pressure* was assigned to column A as shown in Table 4 below. This means that it will only have to be changed once (from low to high) during the experiment. The P, I, and D gains can be configured through the controller interface software. Therefore, ordering these factors from most difficult to easiest for setting changes did not matter. Additionally, randomization for carrying out the experimental runs was not needed since no systematic build-up of variation is expected from changing factors from low to high levels. Table 4 displays the actual levels for the controllable factors as well as the data collected for the *Response Time* in milli seconds as well as the percentage of *Deviation from Target*. The target position was set at 4.895 inches. Actual positions are also included in Table 3 for reference.

Data Analysis

The data from the experiment was analyzed using a statistical software. The analysis includes ANOVA as well as mean plots. It should be mentioned that all three-way interactions and higher are not included in the model and considered negligible (random variation). Therefore, they are used to estimate the error term in ANOVA. The first part of the analysis deals with *Response Time* which should be minimized

Table 4 displays results from ANOVA. Based on the analysis, both the *Derivative Gain* and *Proportional Gain* are statistically significant at α=0.05 level of significance. It is indicated that *Proportional Gain* is highly significant and may require more attention (control) in applications. It

Table 4: Experimental Data

ID	Pressure	Proportional Gain	Integral Gain	Differential Gain	Resp Time (ms)	Position (in)	Dev from Target
1	400	10	0	-100	4,250	4.854	0.838%
2	400	10	0	100	10,000	5.019	2.533%
3	400	10	99.9	-100	6,600	4.859	0.735%
4	400	10	99.9	100	9,600	5.011	2.370%
5	400	1000	0	-100	720	5.311	8.498%
6	400	1000	0	100	720	5.31	8.478%
7	400	1000	99.9	-100	720	5.31	8.478%
8	400	1000	99.9	100	720	5.305	8.376%
9	800	10	0	-100	4,300	4.865	0.613%
10	800	10	0	100	4,700	5.028	2.717%
11	800	10	99.9	-100	5,500	4.908	0.266%
12	800	10	99.9	100	7,000	5.037	2.901%
13	800	1000	0	-100	700	5.296	8.192%
14	800	1000	0	100	700	5.305	8.376%
15	800	1000	99.9	-100	700	5.3	8.274%
16	800	1000	99.9	100	700	5.304	8.355%

should also be mentioned that *Pressure*, although not significant at α=0.05, appears to be important. Figure 5 puts the significance of these factors in perspective. Additionally, the interaction between *Derivative Gain* and *Proportional Gain* in Table 5 shows a significant effect. This means that the impact of changing *Derivative Gain* from low to high or vice versa may depends on the level of *Proportional Gain.* Another interaction that is close to being significant at is *Proportional Gain* and *Pressure*.

Table 5. Analysis of Variance for Response Time

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Der Gain	1	7088906	7088906	6.94	0.046*
Int Gain	1	1856406	1856406	1.82	0.235
Prop Gain	1	133807056	133807056	131.03	0.000*
Pressure	1	5096306	5096306	4.99	0.076
2-Way Interactions					
Der Gain *Int Gain	1	170156	170156	0.17	0.700
Der Gain*Prop Gain	1	7088906	7088906	6.94	0.046*
Der Gain*Pressure	1	2932656	2932656	2.87	0.151
Int Gain*Prop Gain	1	1856406	1856406	1.82	0.235
Int Gain*Pressure	1	150156	150156	0.15	0.717
Prop Gain*Pressure	1	4917306	4917306	4.82	0.080
Error	5	5105781	1021156		
Total	15	170070044			

*Significant at α=0.05 (See Pareto chart and factorial plots)

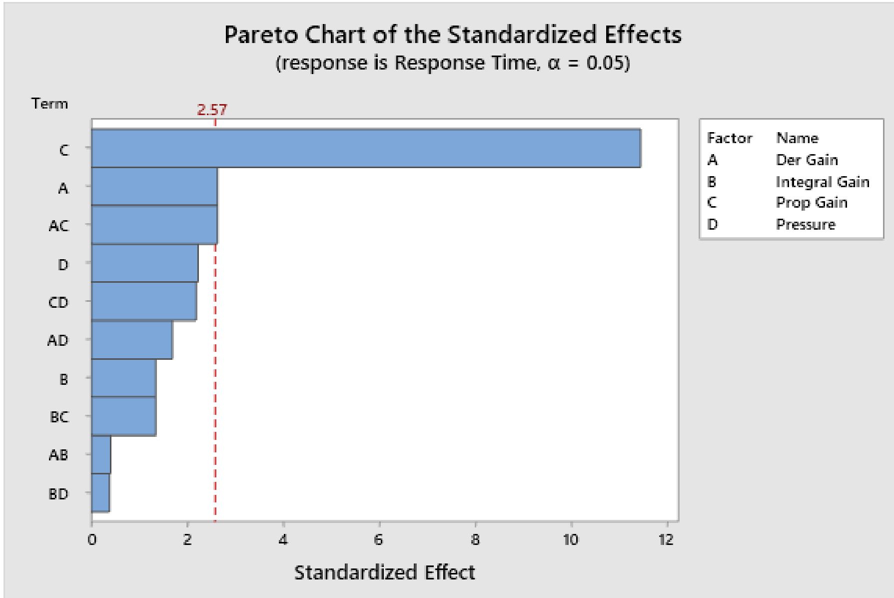

Figure 5: Pareto Chart of Significant Effects for Response Time

The mean plots of factors (main effects) for the *Response Time* are displayed in Figure 6 and the interactions in Figure 7. These figures provide information on whether the statistically significant effects found in the ANOVA table are practically significant. They will also indicate that what levels should the insignificant effects be left at for future experiments

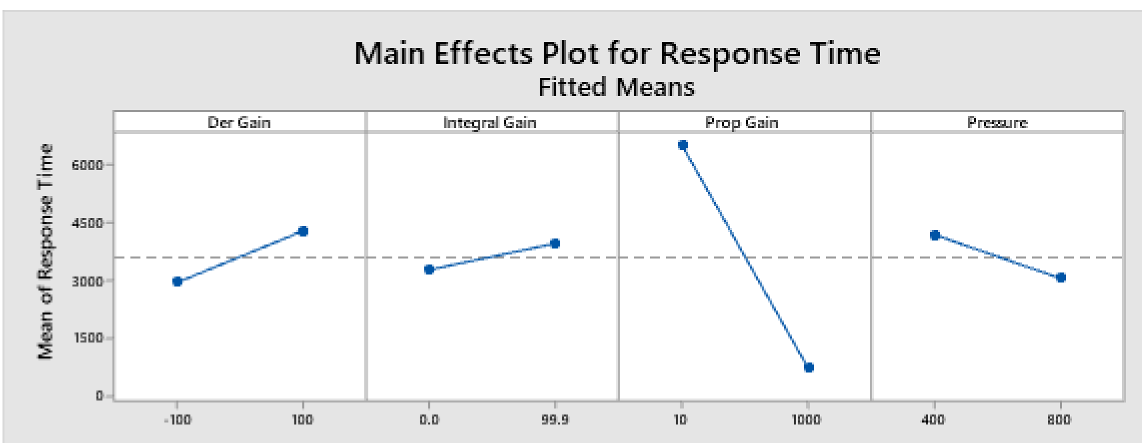

Figure 6: Plots of Factors (Main Effects) for Response Time

The second part of the analysis is related to the percentage of *Deviation from Target,* which should be minimized. Both the *Derivative Gain* and *Proportional Gain* are statistically significant at α=0.05 level of significance as shown in Table 6. It is obvious that *Proportional Gain* is highly significant here as well. Figure 8 puts the significance of these factors in perspective. Additionally, the interaction between *Derivative Gain* and *Proportional Gain* in Table 6 shows a significant effect. This means that the impact of changing *Derivative Gain* from low to high or vice versa may depends on the level of *Proportional Gain.* This means that we should be careful about changing one factor without studying the impact from this interaction. Another interaction that is close to being significant at is *Derivative Gain* and *Pressure*. Figure 10 puts the significance of these factors in perspective.

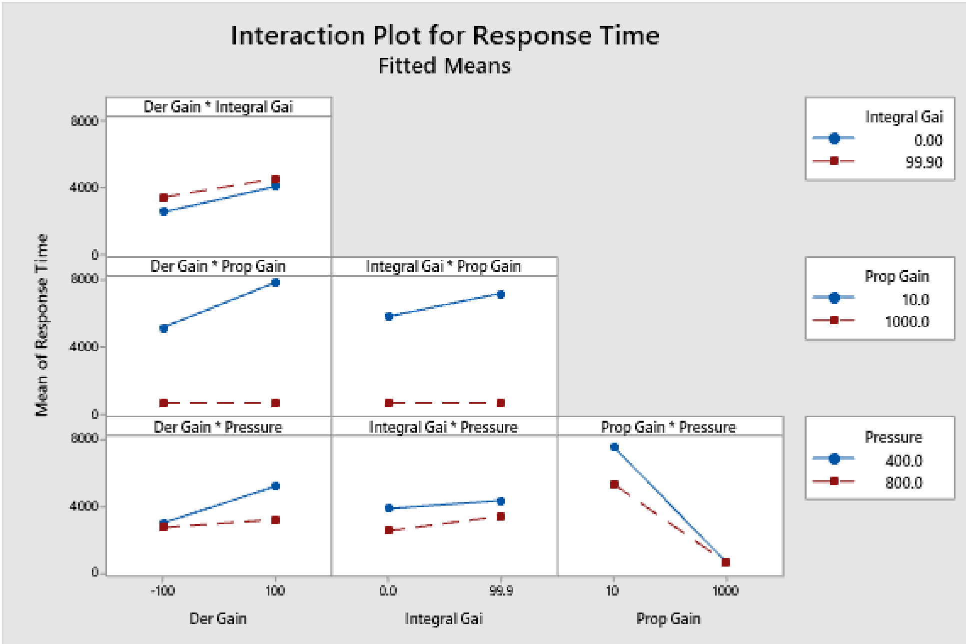

Figure 7: Plots of Interactions for Response Time

Table 6. Analysis of Variance for Deviation from Target

Source	DF	Adj SS	Adj MS	F-Value	P-Value
Der Gain	1	0.000422	0.000422	154.67	0.000*
Int Gain	1	0.000002	0.000002	0.55	0.491
Prop Gain	1	0.018262	0.018262	6701.11	0.000*
Pressure	1	0.000002	0.000002	0.86	0.396
2-Way Interactions					
Der Gain*Integral Gain	1	0.000001	0.000001	0.19	0.683
Der Gain*Prop Gain	1	0.000393	0.000393	144.09	0.000*
Der Gain*Pressure	1	0.000020	0.000020	7.41	0.042*
Integral Gain*Prop Gain	1	0.000001	0.000001	0.31	0.602
Integral Gain*Pressure	1	0.000001	0.000001	0.19	0.683
Prop Gain*Pressure	1	0.000003	0.000003	0.98	0.368
Error	5	0.000014	0.000003		
Total	15	0.019119			

*Significant at α=0.05 (See Pareto chart and factorial plots)

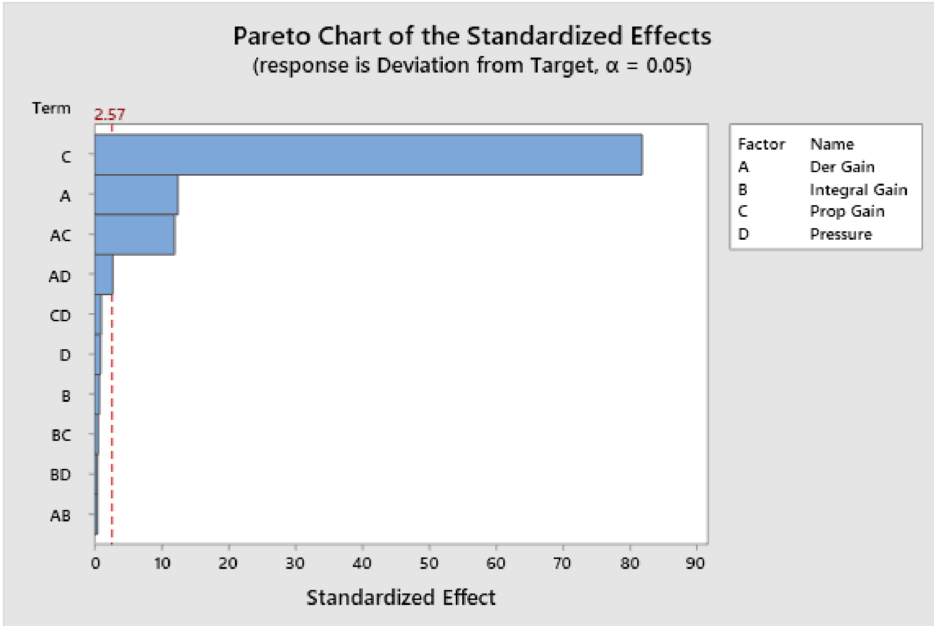

Figure 8. Pareto Chart of Significant Effects for Deviation from Target

The mean plots of factors (main effects) for the percentage of *Deviation from Target* are displayed in Figure 9 and the interactions in Figure 10. As the case for *Response Time,* these figures provide information on whether the statistically significant effects found in the ANOVA table are practically significant. They will also indicate that what levels should the insignificant effects be left at for future experiments.

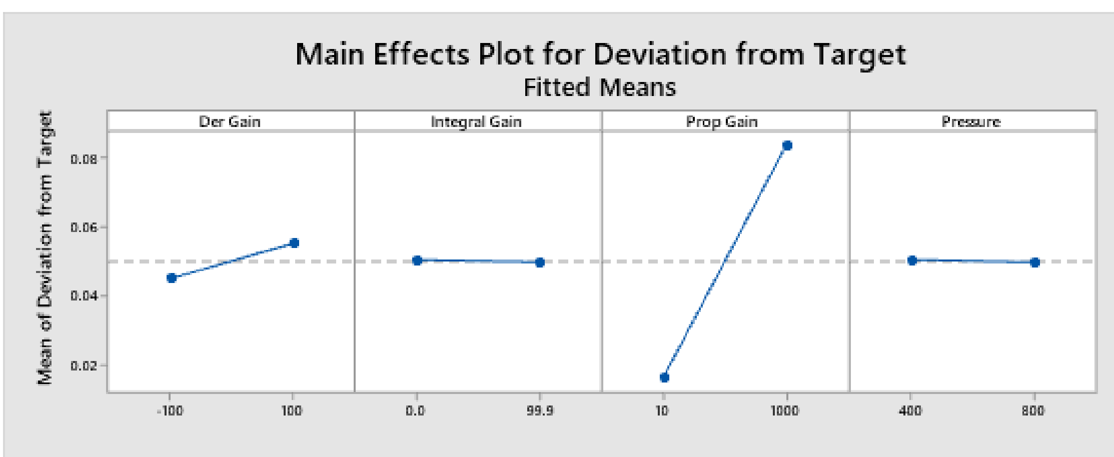

Figure 9: Plots of Factors (Main Effects) for Deviation from Target

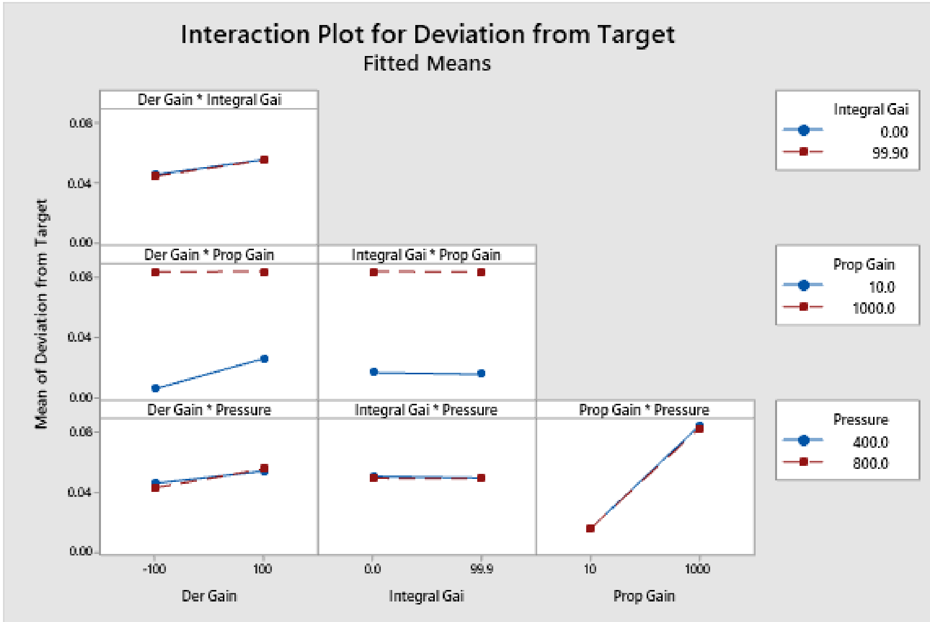

Figure 10: Plots of Interactions for Deviation from Target

Discussion of Results

After evaluating the analyses of both *Response Time* and the percentage of *Deviation from Target*, we can draw the following conclusions:

- The *Proportional Gain* setting has the most significant effect on both *Response Time* and the percentage of *Deviation from Target*. However, there is a conflict here in the fact that increasing the *Proportional Gain* tends to decrease *Response Time*. At the same time, it increases the percentage of *Deviation from Target*. While decreasing the *Response Time* is desirable, increasing the *Deviation from Target* is not.
- The *Derivative Gain* setting seems to decrease both the *Response Time* and *Deviation from Target*. Therefore, keeping the factor at lower settings seems to be desirable.
- While changing the *Pressure* setting from 400 to 800 PSI made no impact on the *Deviation from Target*, it did have an impact of close to one second on *Response Time* (from 3,037 to 4,166 ms). If one second is not practically significant, it may be economically desirable to keep this factor at lower settings.
- *Integral Gain* has no significant effect on either the *Response Time* or *Deviation from Target* and can be set where economically feasible.
- The interactions *Proportional Gain x Pressure* as well as *Derivative Gain x Pressure* on *Response Time* should be considered when setting up the process. The *Pressure* setting has low to no impact on the *Response Time* when *Derivative Gain* is set at the low level. On the other hand, *Pressure* has low to no impact on the *Response Time* when *Proportional Gain* is set at higher levels.

Student Feedback and Future Experiments

This case study was planned to present to students in the Quality Management course for the studying of the DOE method in the spring semester of 2020. The demonstration was done virtually through recorded presentation to students due to COVID-19 situation. Students in the Quality

Management course have learned the DOE method, studied the implementation of this method on this automatic hydraulic position control system, and understood how the results from the study have improved the performance of the actual system. Sampled Feedback from students are listed below.

- "Using the real industry application in teaching quality concepts shows us how valuable real-world application is. Teaching us what we are going to see in the real world, in my eyes, is way more valuable than learning general knowledge about process simulation. It shows us more insight into the real world. It can even give us talking points about being 'Experienced' in that field of knowledge rather than just knowing the basics of Hydraulics"

- "I understood how design of experiments worked from the lecture examples and practice activity, but sometimes implementing something like DOE in real life may be harder to do from the simulation examples than a real example like this. It shows some examples of other factors that can be controlled as well because those will be different for different applications. I think it also helped me understand how to read the interactions better"

- "I believe having real applications like this is a tremendous help in learning about quality and how it is used. We all learn the concepts, but it makes much more sense when we can see it applied in a scenario, we might see in our jobs outside of school. It also shows the interaction between different tools"

- "It's more beneficial to use a real-world application in this instance because it allows us as students to view an application that is currently (or soon to be) used in industry and how quality concepts play a factor. Secondly, it's more valuable to use a real industrial application because it prepares us to handle real-world problems in industry using quality concepts"

To continue this type of implementations in the future, factors determined to be significant will be used in future experiments for optimization. This may include more levels to investigate whether the relationship is linear or nonlinear in nature.

Additionally, and since real-life application may have fluctuation in environmental conditions, ambient temperature included in the experiment to determine its effect and select the best settings that are insensitive to environmental fluctuations. Taguchi methods could be used for such experiments.

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