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Quality Control in System Optimization of an Electrohydraulic System

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Abstract

Electrohydraulic systems with the combination of hydraulic hardware and electronics have offered superior industrial applications in position, velocity, and force/torque control. Position control is the more demanding application of such automated electrohydraulic systems. However, the system performance is affected by many factors with hydraulic and electronic hardware and software and, therefore, impacts the manufacturing process performance and product quality. To optimize the system performance, it is important to identify the key factors that play significant roles. This study presents a quality control application to optimize an electrohydraulic system in the presence of extraneous variability. The performance measures of the system are response time of the cylinder to a target setpoint position and positioning errors that reflect the deviation of current cylinder position from the target position. The controllable process parameters (factors) in this system include fluid pressure, proportional gain of the controller configuration, and signal communication (local vs. remote). The ambient temperature will be used as the extraneous noise variable to simulate real-life manufacturing environment. The objective of the study is to answer the questions: (1) Which factors affect the system performance measures and to what extent? and (2) can optimal settings be identified for the system to perform consistently over the range of the extraneous noise variable? To do this, Taguchi experiments will be utilized, along with Signal to Noise (S/N) ratios and factorial plots, to analyze the results. The aim of this paper is to introduce the application of quality control methods in performance optimization for an automated electrohydraulic position control system. The system setup, hardware, software, and programming will be introduced. The research design, measurements, and experimental runs will be demonstrated and explained. The impact on students' understanding will be analyzed through assessment of their reports and presentations.

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

Introduction

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, a designed experiment using the Taguchi methods was used on an automated hydraulic position control system.

System Overview

The position control electrohydraulic system is the basic hardware part of this research project. It includes two Parker hydraulic servo systems and a Parker automation controller (PAC). The double cylinder hydraulic system allows users to control the cylinder movements by programing PAC following IEC61131-3 standards. Human machine interface can also be programed in PAC visualization environment.

The hydraulic servo systems can achieve closed-loop control to the cylinders [3]. The servo systems support jogging control, positioning control, and velocity control. They can also feedback running status of the cylinders to the upper computer. The communication between hydraulic servo systems and PAC is established on EtherCAT principle. Double Cylinder Hydraulic system includes 1 Parker automation controller, 2 Compax 3F hydraulic servo drivers, 2 Parker series 3L cylinders, 2 proportional directional control valves, 1 hydraulic pump station and 2 Balluff magnetic position sensor as listed in Table 1. The connection schematic diagram is shown as below in Figure 1

Table 1. The list of system components

Name	Component Type	Part #
PAC320	Automation Controller	PAC320-CXX2X-XX
Compax 3F	Servo Drive	C3F001D2F12 I11 T30 M00
	Servo Drive	C3F001D2F12 I11 T30 M00
DF Plus	Proportional Directional Control Valve	D1FPE50FB9NB00 19
	Proportional Directional Control Valve	D1FBB31FC0NF00 19
Parker Series 3L	Hydraulic Cylinder	01.50 F3LLUS23A 12.000
	Hydraulic Cylinder	01.50 F3LLUS23A 12.000
Balluff	Magnetic Position Sensor	Feedback system 0-10V
	Magnetic Position Sensor	Feedback system 0-10V
Parker H-Pak	Hydraulic Pump/Reservoir	H1B2 7T10P0X13909/13

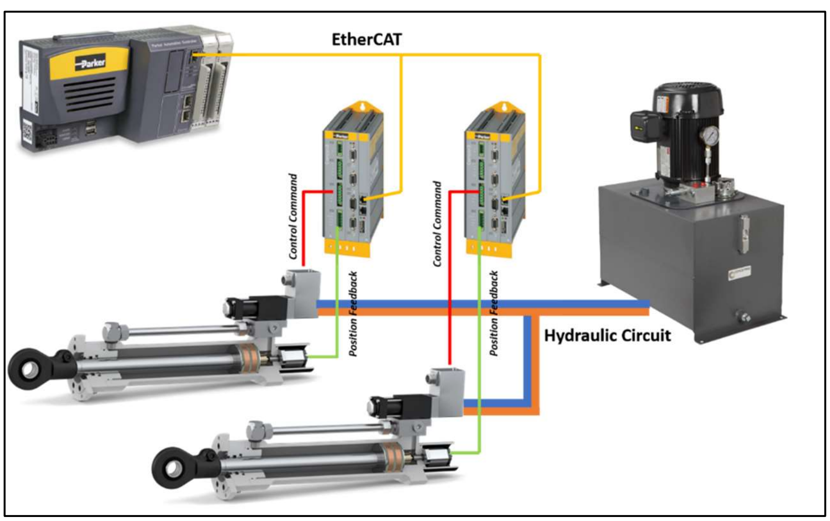

Figure 1. System Structure/Communication

Hardware configuration includes two parts, one is PAC configuration, the other is Compax 3F configuration. EtherCAT of PAC is used as the synchronize communication fieldbus, the PAC configuration is to install EtherCAT devices to the PAC. Figure 2 shows the configuration window of the PAC controller, and the configuration tool for the Compax 3F driver.

The PAC controller and the hydraulic servo drivers are programmed separately. To program the hydraulic servo driver, we need to install and configure the programming environment CodeSys v2.3 and program the servo based on IEC61131-3 standards [4]. As planned, a standard hydraulic servo program was designed to meet most control requirements. In this way, the whole system program can be done only in Parker Automation Manager in the future. The hydraulic servo standard program was designed as below in Table 2.

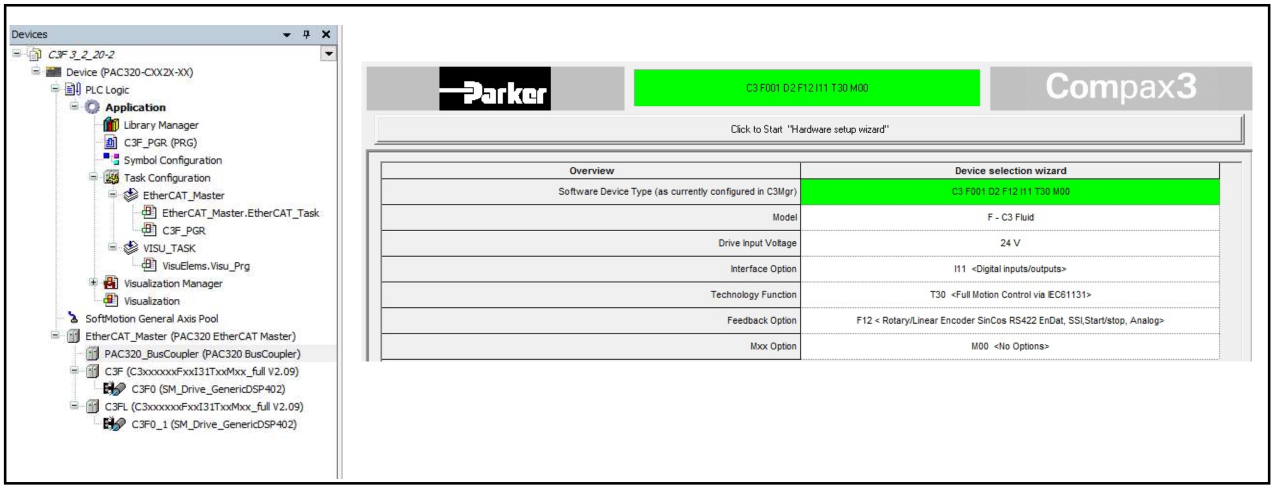

Figure 2. Configuration tool for PAC and Compax3F

Human Machine Interface was designed as shown in Figure 3 which includes following features:

- Power and Reset buttons
- For each cylinder: Enabled, Error, and Motion indicators to let the user know the status of each cylinder
- Jog Forward and Backward buttons to manually position the cylinders
- Home button to fully retract the cylinders
- Actual Position and Velocity outputs that display the real-time values of each cylinder
- Area for the user to manually input a position or velocity command
- Execute button to confirm that command
- Three preset sequences that move both cylinders simultaneously in different ways
- Emergency Stop button

Table 2. The hydraulic servo driver standard program

Function Name	Control Function	Inputs	Outputs
Reset	MC_Reset	Axis(int): axis ID Execute(bool): C3Array.Col03_Row01.0	Done(bool):
Power On	MC_Power	Axis(int): axis ID Enable(bool): C3Array.Col03_Row01.1	Status(bool): C3Array.Col03_Row02.0 Error(bool):
Stop	MC_Stop	Axis(int): axis ID Execute(bool): C3Array.Col03_Row01.2 deceleration (Dint): 200 jerk (Dint): 2000	Done(bool): Error(bool):
Status Feedback	MC_ReadStatus	Enable(bool): True Axis(int): axis ID	Done Error ErrorStop(bool): C3Array.Col03_Row02.1 Stopping Standstill DiscreteMotion: C3Array.Col03_Row02.2 ContinuousMotion: C3Array.Col03_Row02.2 Homing SynchronizeMotion: C3Array.Col03_Row02.2
Positioning	MC_MoveAbsolute	Axis(int): axis ID Execute(bool): C3Array.Col03_Row01.5 CMD Position(real): C3Array.Col06_Row02 CMD Velocity(real): C3Array.Col06_Row01 CMD Acceleration (Dint): 100 CMD Deceleration (Dint): 100 CMD Jerk (Dint): 1000 CMD JerkDecel(Dint): 1000	Done(bool): C3Array.Col03_Row02.3 Aborted(bool): Error(bool): Actual Position (Dint[C4_3]): 0x2104 Actual Velocity (Dint[C4_3]): 0x606C
Velocity Control	MC_MoveVelocity	Axis(int): axis ID Execute(bool): C3Array.Col03_Row01.6 CMD Velocity(real): C3Array.Col06_Row01 CMD Acceleration (Dint): 100 CMD Direction(int) (1: positive; 3: negative): C3Array.Col05_Row01	InVelocitybool): C3Array.Col03_Row02.4 Aborted(bool): Error(bool): Actual Position(Dint[C4_3]): 0x2104 Actual Velocity(Dint[C4_3]): 0x606C
Jog	C3_Jog	Axis(int): axis ID JogForward(bool): C3Array.Col03_Row01.3	Busy(bool): Error(bool): Actual Position(Dint[C4-3]): 0x2104

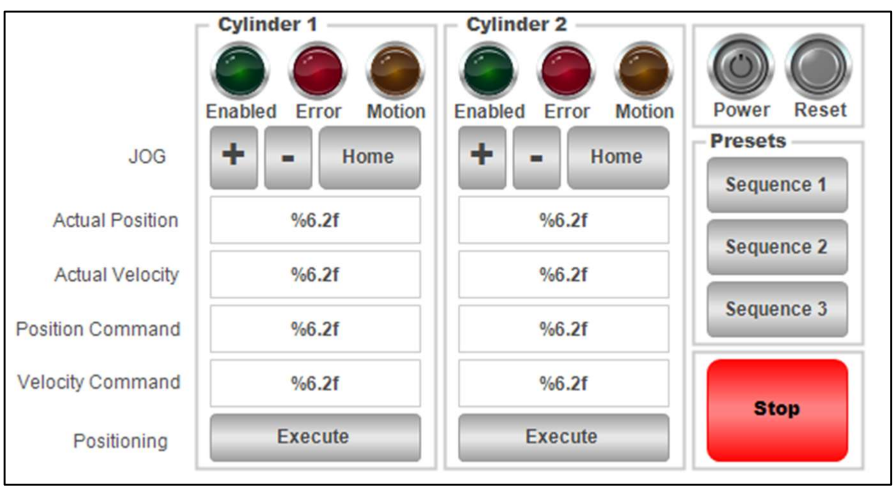

Figure 3: Human – Machine Interface

Design of Experiments

According to W. Edwards Deming, prediction requires theory and builds knowledge through systematic revisions based on comparison of prediction with observation [5]. For example, a process setup requires instructions or a procedure to ensure that it delivers the desired outcome. In other words, a certain outcome can be predicted when procedural steps are performed as prescribed. The outcome (e.g., product or service) is then compared to what is expected. 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]. The PDSA cycle is continuous and thus guarantees the temporal dimension for the theory of knowledge. In other words, knowledge is gained through experimentation after each cycle and future cycles are undertaken with accumulated knowledge. 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].

While one-factor-at-a-time is commonly used for experimentation in industry, 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 3 shows the phases of the PDSA cycle along with what each phase involves when using the DoE methodology.

Table 3: PDSA Details

Phase	Description
Plan (P)	• Identify controllable factors affecting performance. • Identify noise factors. • Identify performance (response) variables. • Design the experiment (e.g., factorial, fractional factorial design, Taguchi's orthogonal array)
Do (D)	• Run the experiment (randomize if necessary) • Collect data
Study (S)	• Analyze data graphically and statistically. • Use earlier analysis if available 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)

Taguchi Methods

Dr. Genichi Taguchi classified quality as two types: features that the customer wants and problems the customer does not want [9]. To achieve both, process optimization so that products can be made with the least amount of variation is needed. Taguchi refers to this methodology as *Parameter Design*, which is the ability to design a process that is least sensitive to environmental changes (noise). These changes, which include factors like ambient temperature, humidity, and equipment limitations, among others, may be impossible or too costly to control. However, by utilizing Taguchi's *Parameter Design* through his orthogonal arrays (OA), it is possible to select a process setup that is least sensitive to noise.

Taguchi argues that the only measure of robustness (minimum sensitivity to environmental changes) in the design of a process or a product is signal-to-noise (S/N) ratios. The ratio is determined by dividing the value of the response average (signal) by the variability (noise) for a given experimental combination. Since the value of the response will be evaluated through the mean values to be close to the target value, the idea is to minimize the noise (variability) which would in turn maximize the S/N ratio. In any case, the S/N ratios can be applied to investigate the robustness for three different scenarios:

1. *Nominal is Best*: this is used for typical quality characteristics with a target value (nominal) plus equal tolerance on both sides that makes the upper and lower specification limit (USL and LSL, respectively). Examples include viscosity, clearance, etc.
2. *Smaller is Better*: This type is used for situations where the quality characteristic should be minimized as there is only an upper specification limit. Examples include contamination level, shrinkage, and noise level, among others.
3. *Larger is Better*: This type is used for situations where the quality characteristic should be maximized as there is only a lower specification limit. Examples include material strength and fuel efficiency.

The Electrohydraulic System Experiment

In a closed-loop electrohydraulic position control system, performance is commonly analyzed based on the step response time (rise time) and the steady-state error. The step response time is defined as the time the system responds 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 experiment, the response or dependent variables of step response time (STR) and position accuracy represented by position deviation from target (PDT) are measured and analyzed. The STR will be measured in seconds while the position deviation from (PDT) will be presented as the absolute deviation in inches from the target position of 4.0 inches.

Since it is desirable to minimize both the STR and PDT, *Smaller is Better* (SB) scenario will be used to evaluate performance data for each dependent variable. Taguchi uses the following formula for signal-to noise calculations:

$$S/N_{SB} = -10\ log_{10}\left(\frac{\Sigma y^2}{n}\right)$$

Where *n* is the number of observations across all environmental conditions.

The experiment involves 4 controllable factors; one at 4 levels and the other three are at two levels each as shown in Table 4.

Table 4: Controllable Factors and Levels

Controllable Factor	Level			
	1	2	3	4
A: Flow Rate (inches / sec)	1.0	2.0	3.0	4.0
B: Load (lbs.)	0.0	95.0		
C: Hydraulic Pressure (psi)	800	600		
D: Control Access	Local	Remote		

Based on the number of factors and levels to be investigated in this study and the desire to determine the effects of certain interactions, the L_{16} OA design was selected, which includes 16 different combinations. In addition to determining the effects of the controllable factors, the interaction effects of *Flow Rate vs. Load* (AXB) as well as *Load vs. Pressure* (BXC) will also be determined. The experiment was run at two different environmental conditions the were created in the lab. The first condition is a cooler temperature between 60 and 70 °F while the other is at higher ambient temperature range of 90 to 100 °F. The higher temperature was accompanied with humidity that was forced into the room using a humidifier. Tables 5 and 6 display the L_{16} with SRT and PDT data, respectively.

Analysis of Experiment

The analysis for both the SRT and PDT data were carried out using a statistical software with the capability of analyzing S/N ratios. S/N. The S/N ratios are determined using the S/N_{SB} equation stated in the previous section using the observations at the level of interest. For example, the S/N ratio in the SRT data for level 1 of factor *A: Flow Rate* is determined using all 24 observations in rows 1, 2, 13, and 14, where level 1 of *Flow Rate* is present in Table 5 as follows:

$S/N = -10\ \log_{10} [(5.590^2 + 5.590^2 + \ldots.\ 5.615^2 + 5.605^2)/24] = -14.882$

Higher S/N ratios are desirable since it indicates that variation across environmental changes is smaller.

Table 5: Response Time Experimental Data

Run	Controllable Factor				Response Time (Seconds)					
	A Flow Rate	B Load	C Pressure	D Access	at Low Temp (60-70 F)			at High Temp (90-100 F)		
1	1	1	1	1	5.590	5.590	5.375	5.400	5.420	5.410
2	1	2	1	1	5.565	5.385	5.400	5.515	5.470	5.515
3	2	1	1	1	3.435	3.410	3.420	3.450	3.445	3.450
4	2	2	1	1	3.435	3.510	3.435	3.535	3.545	3.515
5	3	1	1	2	2.745	2.745	2.770	2.820	2.770	2.770
6	3	2	1	2	2.780	2.785	2.810	2.950	2.810	2.795
7	4	1	1	2	2.435	3.325	2.410	2.480	2.455	2.435
8	4	2	1	2	2.505	2.435	2.470	2.505	2.480	2.480
9	3	1	2	1	2.955	2.930	2.865	3.000	3.010	3.000
10	3	2	2	1	2.990	3.050	3.025	3.060	3.105	3.035
11	4	1	2	1	2.590	2.615	2.590	2.650	2.675	2.640
12	4	2	2	1	2.660	2.650	2.665	2.785	2.725	2.725
13	1	1	2	2	5.590	5.600	5.615	5.715	5.640	5.665
14	1	2	2	2	5.625	5.615	5.615	5.610	5.615	5.605
15	2	1	2	2	3.550	3.590	3.575	3.625	3.650	3.675
16	2	2	2	2	3.675	3.550	3.675	3.640	3.670	3.635

Table 6: Position Accuracy Experimental Data

Run	Controllable Factor				Position Deviation from Target (absolute values)					
	A Flow R.	B Load	C Pressure	D Access	at Low Temp (60-70 F)			at High Temp (90-100 F)		
1	1	1	1	1	0.002	0.010	0.019	0.058	0.052	0.044
2	1	2	1	1	0.037	0.035	0.035	0.059	0.066	0.053
3	2	1	1	1	0.031	0.019	0.019	0.041	0.051	0.047
4	2	2	1	1	0.031	0.039	0.036	0.060	0.052	0.048
5	3	1	1	2	0.038	0.038	0.044	0.070	0.057	0.029
6	3	2	1	2	0.039	0.034	0.035	0.044	0.024	0.039
7	4	1	1	2	0.043	0.044	0.043	0.034	0.028	0.055
8	4	2	1	2	0.042	0.040	0.038	0.056	0.059	0.052
9	3	1	2	1	0.030	0.042	0.039	0.026	0.052	0.046
10	3	2	2	1	0.031	0.031	0.035	0.044	0.031	0.035
11	4	1	2	1	0.062	0.035	0.042	0.053	0.050	0.046
12	4	2	2	1	0.041	0.037	0.038	0.060	0.044	0.050
13	1	1	2	2	0.008	0.008	0.032	0.064	0.050	0.033
14	1	2	2	2	0.037	0.036	0.035	0.049	0.043	0.049
15	2	1	2	2	0.040	0.045	0.033	0.044	0.040	0.055
16	2	2	2	2	0.035	0.038	0.034	0.038	0.047	0.053

The S/N and Means tables include the "Delta" and "Rank" numbers. A "Delta" value for a given factor is the difference between the highest and the lowest S/N ratios across all levels of that factor and calculated similarly for the Means. A "Rank" determines the ranking of significance for controllable factors with 1 being the most significance based on the "Delta" value. The ranking does not indicate the degree of significance for a given factor.

1. Step Response Time (SRT)

Tables 7 presents the S/N analysis for the SRT data. It indicates that the *Flow Rate* is ranked as first (1) in terms of significance. This was predicted by the experimenters, but it was desirable to see the effect plot across levels. Since it is desirable to have higher S/N ratios, the highest S/N ratio (i.e., consistency of the output) is best at the highest level for *Flow Rate* (4 inches/sec.). It is important to see where the mean is for the desirable level (level 4). Table 8 shows that level 4 has the least SRT mean, which is also desirable since the objective is to minimize the response time or SRT. The second factor in the SRT ranking is *C: Pressure* where level 1 shows a slightly higher SRT value. It is also shown that level 1 (800 psi) produced faster SRT. The other two factors *B: Load* and *D: Access* showed very little difference across their levels in both the S/N ratios and the SRT Means. These results are confirmed in Figures 4 and 5. The interaction plots for *Flow Rate vs. Load* (AXB) as well as *Load vs. Pressure* (BXC) in Figure 6 show no presence of interaction effects when it comes to SRT (lines are parallel or close to parallel for each plot).

Table 7: Signal to Noise (S/N) Ratios for SRT

Level	A-Flow Rate	B-Load	C-Pressure	D-Access
1	-14.882	-10.831	-10.649	-10.904
2	-10.992	-10.882	-11.063	-10.809
3	-9.240			
4	-8.311			
Delta	6.571	0.051	0.414	0.095
Rank	1	4	2	3

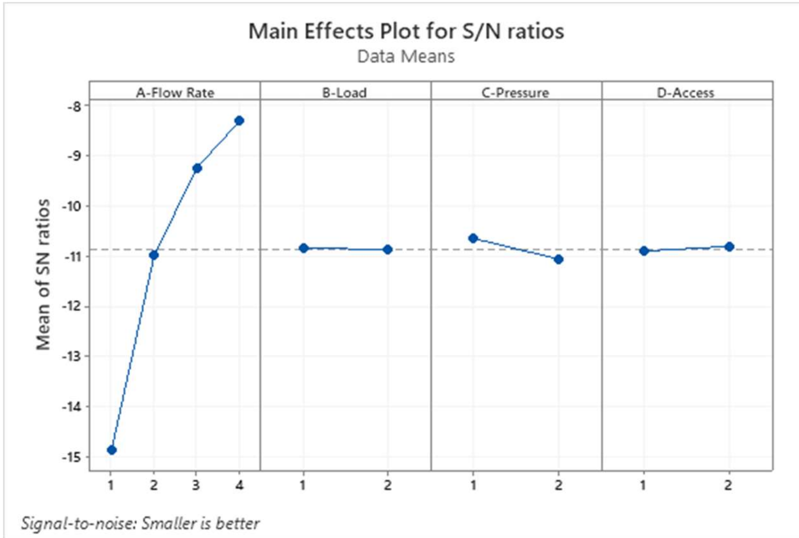

Figure 4: SRT Factor Plots for S/N Ratios

Table 8: Step Response Time (SRT) Means

Level	**A-Flow Rate**	**B-Load**	**C-Pressure**	**D-Access**
1	5.548	3.637	3.566	3.650
2	3.546	3.659	3.729	3.646
3	2.899			
4	2.599			
Delta	2.948	0.022	0.163	0.005
Rank	1	3	2	4

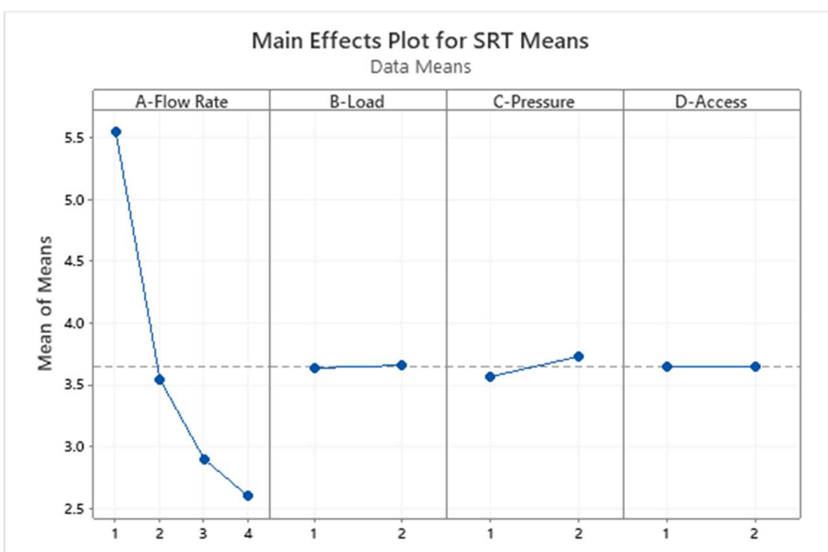

Figure 5: Factor Plots for Response Time

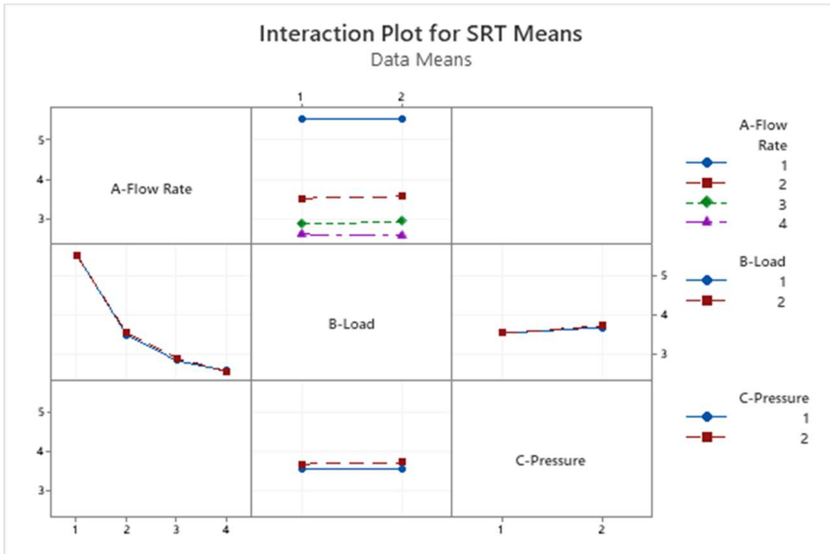

Figure 6: Interaction Plots for Response Time

2. Position Deviation from Target (PDT)

Table 9 displays the S/N analysis for the PDT data. Like the SRT data, here again the analysis indicates that the *Flow Rate* is ranked first in terms of significance. Since it is desirable to have higher S/N ratios, the highest S/N ratio (i.e., consistency of the output) is best at the level 3 for *Flow Rate* (3 inches/sec.). It is important to see where the PDT mean is for the desirable level (level 3). Table 10 shows that level 1 has the lowest PDT mean (0.03808 inches) but very close to level 3 with a PDT mean of 0.03887 inches. Note here that the closer the deviation from target is to zero, the better. The second factor in the PDT ranking is *C: Pressure* where level 2 shows a slightly higher S/N value. In Table 10, it also shows that level 2 (600 psi) to be a more desirable PDT mean (closer to zero). Note that factor *B: Load* had a more significant impact on PDT than factor *C: Pressure* in mean values and was very close third for S/N value. Factor *D: Access* showed very little difference between levels in both the S/N ratios and the Means. These results are confirmed in Figures 7 and 8.

The interaction plots for *Flow Rate vs. Load* (AXB) as well as *Load vs. Pressure* (BXC) in Figure 9 show the presence of interactions (lines cross or have the tendency to cross). For *Flow Rate vs. Load* (AXB), there seems to be more consistency in PDT for both levels of *Load* when the *Flow Rate* is set at levels 2 or 4. For *Load vs. Pressure* (BXC) interaction, there seems to be more consistency across loads when the pressure is set at level 2 (600 psi).

Table 9: Signal to Noise Ratios for fraction PDT

Level	A-Flow Rate	B-Load	C-Pressure	D-Access
1	27.64	27.60	27.40	27.54
2	27.61	27.41	27.62	27.47
3	28.06			
4	26.71			
Delta	1.35	0.19	0.22	0.07
Rank	1	3	2	4

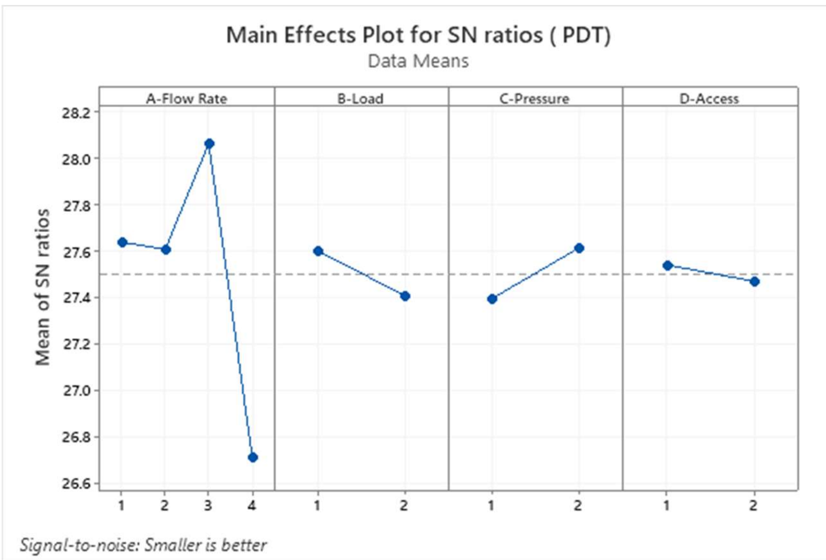

Figure 7: PDT Factor Plots for S/N Ratios

Table 10: Position Deviation fraction (PDT) Means

Level	A-Flow Rate	B-Load	C-Pressure	D-Access
1	0.03808	0.03940	0.04102	0.04050
2	0.04067	0.04217	0.04054	0.04106
3	0.03887			
4	0.04550			
Delta	0.00742	0.00277	0.00048	0.00056
Rank	1	2	4	3

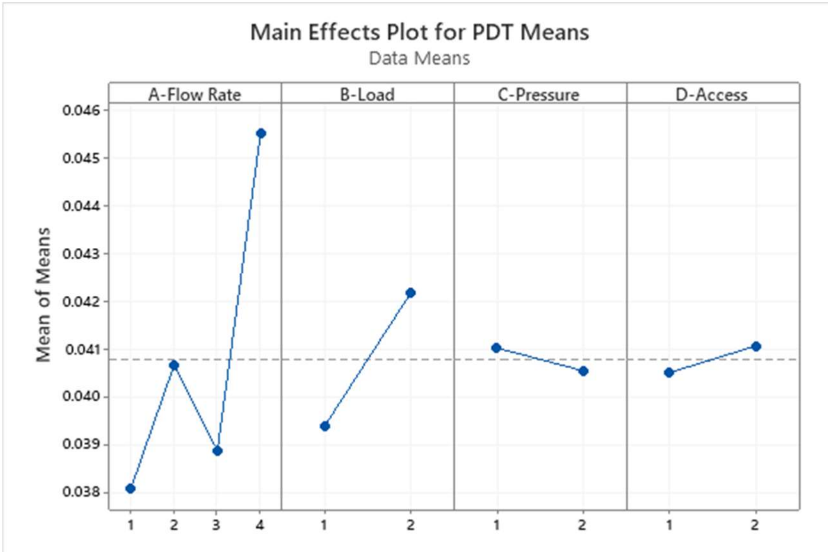

Figure 8: Factor Plots for Position Accuracy

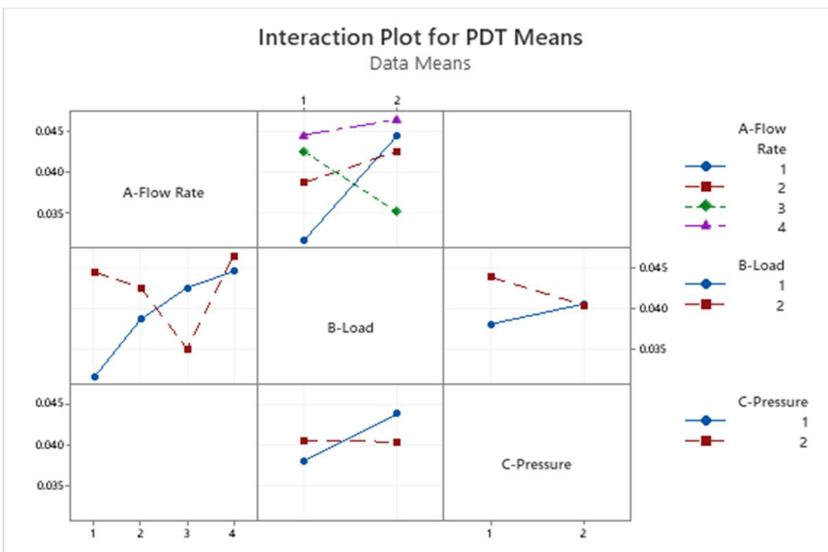

Figure 9: Interaction Plots for Position Accuracy

Discussion of Results & Concluding Remarks

The study at hand using Taguchi's orthogonal arrays had two dimensions of competing objectives. The first comes from evaluating both the S/N ratios and means to identify the best setting for a given factor. The other dimension is related to having more than one response to evaluate – namely the SRT and PDT. In other words, if one level works best for the SRT means, it might not for the SRT S/N ratios. Similarly, if one level gives best results for the SRT objective, it might not be the same level for the PDT objective. Therefore, tradeoffs are common in such situations so that improvements can be made. Tradeoffs can be made by asking the following questions: If the difference between levels is significant, is it also practical? which response is more important for an application, SRT or PDT? And, if there is no significant difference between levels of a given factor, which level is more economical?

Based on these questions, and possibly others that maybe organization-specific, the best parameter settings for a process can be established. Table 11 shows the best settings for the two dimensions mentioned above then the best overall settings. For the *Flow Rate*, although level 4 appears twice, the difference between levels 3 and 4 is minimal and it would be more economical to set it at 3 inches per second. For *Load*, the S/N difference seems very minimal compared to the means difference in the PDT means. As for the Pressure, the best setting should be 600 psi based on both the difference in S/N and means as well as economics. For controller *Access*, it can be either level but given the choice, it is probably better to have access locally (hard-wired) to avoid any potential network issues when done remotely.

Table 11: Best Settings

Response	Data	Best Level			
		A: Flow Rate	B: Load	C: Pressure	D: Access
Step Response Time (SRT)	S/N Ratio	4	1	1	1 or 2
	Means	4	1	1	1 or 2
Deviation from Target (PDT)	S/N Ratio	3	2	2	2
	Means	1	1	2	1
Best Overall Settings		**3**	**1**	**2**	**1**

As shown in this study, using design of experiments with Taguchi's orthogonal arrays in an engineering laboratory is a great way for diving deeper and generating critical thinking opportunities for students. It allows students to conduct experiments and figure out the impact of both controllable and noise factors on performance. For competing objectives, it also allows students to make decisions based on tradeoffs to determine best settings. Another takeaway from this is to take the best overall settings and run a confirmation experiment across environmental conditions.

In addition to sharing the results of this experiment with students in the Quality Management Systems class, students will have the opportunity to conduct such work themselves. The goal is to have students utilize the Taguchi techniques for completing quality improvement projects using the Automatic Electrohydraulic System. Such hands-on problem-solving projects can be more appealing to students enrolled in the Quality Management Systems course who are enrolled or have already completed the Hydraulics and Pneumatics course. The Taguchi techniques presented in this paper can be utilized to further students' knowledge about the Electrohydraulic System while completing hands-on quality improvement projects. Project results can then be presented in the class for further discussion to enhance knowledge of both the electrohydraulic system and the quality improvement techniques. Additionally, this work can be extended to other labs within the department so there are more options for quality improvement projects.

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