TOTAL DESIGN CONCEPT TO ROBOTIC QUALITY

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ABSTRACT

A new prospect is introduced in this study by considering robot accuracy as a performance quality characteristic. A robust design is constructed through experimental design of Taguchi method as well as Monte-Carlo simulation. The aim of this work is to reduce the robot rotational and translational accuracy variations. The concept of employing inner and outer orthogonal arrays is introduced. The significant parameters are identified and to select the optimal tolerance range for each parameter for a specific point in the workspace of a PUMA-type manipulator. The signal-to-noise ratio and the orthogonal arrays are used to evaluate the accuracy performance. Moreover, the fractional factorial results are compared with the full factorial results.

Keywords: Total quality, Quality improvement, Robot kinematics, Design methodology

INTRODUCTION

The total quality at the design stage (total design) is introduced in this work. It can be split into two main categories. First, the design optimization (robust design) in which the product variation is reduced around the target characteristic. Second, the performance evaluation which is the process of attaching a monetary value to quality.

Robust design problem was discussed by many researchers. Bhatti and Rao[1] used both analytical methods and Monte-Carlo simulation techniques to analyze robot manipulator. They stated that the Monte-Carlo simulation is more accurate than the analytical methods. They also found that the analytical methods for design optimization are not efficient for robot manipulators. Eggert and Mayne[2] proved that Monte-Carlo simulation [3] requires large number of computations for small problems. This limited Bhatti to work with simple cases. Liou *et al.* [4] used Taguchi methods [5] for a two-links manipulator for specific points in workspace. They reduced the computation time with maintaining high accuracy level.

The objective of this study is to maximize the quality characteristic which is the robot accuracy or, in other words, to minimize the end-effector rotational and translational deviations for a PUMA-560 manipulator. Both Taguchi method and Monte-Carlo simulation are used.

Experimental design and data analysis are performed. Inner and outer orthogonal arrays are used to make the design less sensitive to the variation. This improves reliability and reduces the manufacturing costs. The orthogonal array selection, number of factors, their levels, column assignments and factor interactions are considered. Data transformation Signal-to-noise (S/N) ratio which consolidates the repetitive data into one value is also used. The S/N of smaller the better type of characteristic is applied to both fractional factorial and full factorial

OVERVIEW AND DEFINITIONS

This section provides an overview for most of the used total quality terms. The *controllable factors* are assigned for the manipulator kinematic parameters errors (tolerance ranges). In the current analysis, the controllable parameters are specified for the link lengths errors (LE's) and joints misalignment vectors (JE's). On the other hand, the *uncontrollable factors* are specified for tolerance signs (noises).

Full Factorial indicates employing all factors (parameters) with all possible alternative errors and noises. Likewise, the *fractional factorial* indicates employing all factors with some alternative errors and noises. The *orthogonal array* (OA) is a family of arrays developed from the fractional factorial experiments. It could be inner or outer. The inner orthogonal array contains the controllable parameters while the outer orthogonal array contains the uncontrollable parameters. The objective of the inner orthogonal array is to determine the significance of controllable parameters and to select their levels to optimize the performance measure. Moreover, the objective of the outer orthogonal array is to introduce the noise produced by controllable parameters. The convention for naming those arrays is L#; where # is the number of experiment trials. Examples for the orthogonal arrays are L16 and L32. The *Signal-to-Noise* (S/N) ratio is developed as the objective function for optimization. It consolidates several data into one value that reflects the amount of variation.

Taguchi method uses both the orthogonal arrays and signal-to-noise to measure the system performance. It selects and identifies the controllable and uncontrollable parameters to study how significant these parameters could affect the performance measure. On the other hand, Monte-Carlo method uses computer routines to generate instances of random variables according to their specified distribution types and characteristics. The algorithm for Monte-Carlo simulation could be classified as

1. Identifying the various random variables of robot kinematic parameters (L's and J's).
2. Assuming all random variables follow the normal distribution.
3. Generating a uniformly distributed random number for each kinematic parameter.
4. Evaluating performance measure, such as the position error of the manipulator.
5. Performing steps (1) through (4) n-times.

Finally, the analysis of variance (ANOVA) is used as a statistical analysis technique for identifying and measuring the various sources of variation within a collection of data.

ROBUST DESIGN

Ten independent factors contain four links lengths (L's) and six joints alignment vectors (J's) are chosen for a PUMA-type manipulator. Their nominal values are shown in Table 1. More kinematic models details could be found in References 7 and 8. In using Taguchi method, the discrete tolerance ranges (LE and JE) are either two (0.05% and 0.1%) or three levels (0.02%, 0.05% and 0.1%). Theses ranges are chosen based on experimental work results[8]. The actual parameters values are fluctuating at these levels around their nominal values.

The first experimental design is performed for an L16 inner orthogonal array of ten parameters (i.e., resolution 1) with two levels of tolerance ranges Table 2. T stands for tight tolerance (T = 0.05%) and L stands for loose tolerance (L = 0.1%). The outer orthogonal array is then constructed, in this case, by replacing T by N (for negative tolerance) and L by P (for positive tolerance). The inner and outer orthogonal arrays together specify a set of factor values. Those values contain the ten nominal parameters plus or minus the tolerance ranges ($Li \pm LEi$ and/or $Ji \pm JEi$). They yield a new (16×16) array. Each element of this new array is produced from an individual computer run. For instant, element (i, j) is produced from the i^{th} row of the inner array and the j^{th} column of the outer array. Hence, the required number of trials to construct the new array is $16\times16 = 256$.

Table 1 Nominal link dimensions and joint alignment vectors

Link	Symbol	Nominal Link Dimension	Joint	Symbol	Nominal Joint Alignment Vector		
					u_x	u_y	U_z
2	L1	254	1	J1	0	0	1
3	L2	431.8	2	J2	0	1	0
4	L3	431.8	3	J3	0	1	0
5	—	0	4	J4	0	0	1
6	—	0	5	J5	0	-1	0
7	L4	127	6	J6	0	0	-1

Table 2 L16 inner OA containing the controllable parameters

Trial #	JE1	JE2	JE3	JE4	JE5	JE6	LE2	LE3	LE4	LE7
1	T	T	T	T	T	T	T	T	T	T
2	T	T	T	L	L	T	L	L	T	L
3	T	T	L	L	T	L	L	T	L	T
4	T	T	L	T	L	L	T	L	L	L
5	T	L	T	T	T	T	L	L	L	T
6	T	L	T	L	L	T	T	T	L	L
7	T	L	L	L	T	L	T	L	T	T
8	T	L	L	T	L	L	L	T	T	L
9	L	T	T	T	T	L	L	T	L	L
10	L	T	T	L	L	L	T	L	L	T
11	L	T	L	L	T	T	T	T	T	L
12	L	T	L	T	L	T	L	L	T	T
13	L	L	T	T	T	L	T	L	T	L
14	L	L	T	L	L	L	L	T	T	T
15	L	L	L	L	T	T	L	L	L	L
16	L	L	L	T	L	T	T	T	L	T

The signal-to-noise (S/N) ratio is used as a data transformation method to consolidate the repetitive data into one value [9]. This value reflects the mean and the amount of variation. The S/N equation of smaller is the better type of characteristic (y), which is the manipulator end-effector deviations, can be calculated as follows:

$$S/N = -10 \log \left(\frac{1}{n} \sum_{i=1}^{n} y_i^2 \right) \qquad (1)$$

The tolerances of the ten factors are considered as manufacturing errors. Hence, they do not vary during robot motion. The desired position of the end-effector is assumed to be X = 560, Y = 0 and Z = -130 in a global Cartesian coordinate system. Our objective is to minimize the end-effector rotational and translational deviations.

The second experimental design is fulfilled for an L32 as an inner orthogonal array. Three levels with 0.02%, 0.05% and 0.1% tolerance ranges are applied. The ANOVA table for both L16 and L32 is shown in Table 3. Where, DOF is the degrees of freedom, SS is the sum of squares and P is percentage contributions.

The third experimental design is done by developing an extended Taguchi method. In this condition, the inner orthogonal array is constructed by using a full factorial with two levels of 0.05% and 0.1% tolerance ranges. The ANOVA table is shown in Table 4.

In using Monte-Carlo simulation, the tolerance ranges are assumed to be normally distributed over six times the given standard deviations ($\mu \pm 3\sigma$) with more than 99% confidence. To compare the efficiency between using Taguchi method and Monte-Carlo simulation, the same conditions as in Taguchi first trial are utilized. The S/N ratio is calculated to Monte-Carlo with a tolerance range of 0.05%. The manipulator end-effector deviations varieties are calculated 5,000 times using ten standard normally distributed randoms as follows:
The k^{th} perturbed parameter is

$$\overleftrightarrow{X}_k = X_k \pm \sigma_{\overleftrightarrow{X}_k} \times Z_k \tag{2}$$

where,

$\overleftrightarrow{X}_k$ is the perturbed parameter,
X_k is the nominal parameter,
Z_k are standard normally distributed random varieties,
$\sigma_{\overleftrightarrow{X}_k}$ is the standard deviation for X and could be defined as

$$\sigma_{\overleftrightarrow{X}_k} = X_k \times \xi_X^{\%} \tag{3}$$

where $\xi_X^{\%}$ is the percent error.

Table 3 ANOVA table for L16 and L32 orthogonal arrays

Errors	DOF	L16 Orthogonal Array Rotation		L16 Orthogonal Array Translation		L32 Orthogonal Array Rotation		L32 Orthogonal Array Translation	
		SS	P	SS	P	SS	P	SS	P
JE 1	2	112.05	20 %	118.62	9 %	80.87	12 %	115.62	9 %
JE 2	2	56.02	10 %	303.13	23 %	94.35	14 %	303.13	24 %
JE 3	2	100.84	18 %	289.95	22 %	107.83	16 %	289.95	22 %
JE 4	2	84.04	15 %	105.44	8 %	114.56	17 %	105.44	8 %
JE 5	2	61.63	11 %	92.26	7 %	107.83	16 %	92.26	7 %
JE 6	2	44.82	8 %	79.08	6 %	94.35	14 %	79.08	6 %
LE 2	2	22.41	4 %	79.08	6 %	20.21	3 %	79.08	6 %
LE 3	2	16.81	3 %	118.62	9 %	26.95	4 %	108.62	8 %
LE 4	2	50.42	9 %	65.90	5 %	13.47	2 %	65.90	5 %
LE 7	2	11.21	2 %	65.90	5 %	13.47	2 %	65.90	5 %
Error	6	93.70		90.80		93.70		90.80	
SS_t		653.94		1408.76		767.64		1395.76	

Table 4 ANOVA table for full factorial

Errors	DOF	Rotation SS	Rotation P	Translation SS	Translation P
JE 1	2	988.47	15 %	1109.55	4 %
JE 2	2	1317.96	20 %	10818.10	39 %
JE 3	2	1054.37	16 %	11095.49	40 %
JE 4	2	1186.17	18 %	1109.55	4 %
JE 5	2	988.47	15 %	832.16	3 %
JE 6	2	1054.37	16 %	832.16	3 %
LE 2	2	13.16	0 %	110.96	0 %
LE 3	2	15.76	0 %	1386.94	5 %
LE 4	2	11.25	0 %	554.78	2 %
LE 7	2	9.68	0 %	55.48	0 %
Error	6	985.97		198.60	
SS_t		7625.66		27905.16	

Equations 2 and 3 can be remodeled t match the current analysis as follows

$$\overleftrightarrow{\mathbf{u}}_k = \frac{\text{sign}(u_{k_i})}{\left\|\overleftrightarrow{\mathbf{u}}_k\right\|}\left[\xi^{\%}_{u,k}.Z_k\left\|\mathbf{u}_k\right\| + \left|u_{k_i}\right|\right] \tag{4}$$

$$\overleftrightarrow{\mathbf{b}}_k = \text{sign}(b_{k_i})\left[\xi^{\%}_{b,k}.Z_k\left\|\mathbf{b}_k\right\| + \left|b_{k_i}\right|\right] \tag{5}$$

where $\mathbf{u}_k$ is the k^{th} Joint Axes Alignmer Vector and $\mathbf{b}_k$ is the k^{th} link body vector
Figure 1 shows the S/N ratio comparison the first trial result between the tw

methods. From that figure, the S/N ratio resulting from Monte-Carlo simulation becomes steady after 2,000 calculation times. This implies that this number of calculations is sufficient in this case.

In order to compare Taguchi with Monte-Carlo trial by trial and avoid confounding, the inner array of the Taguchi method will have to be at least two-way interaction.

For each trial of the fixed maximum tolerance (0.1%), Taguchi method is performed only 1 time, while Monte-Carlo is performed 5,000 times with normally distributed random tolerances. The difference between the two methods is insignificant.

EVALUATION OF PERFORMANCE

The total design second category is the process of attaching a monetary value to quality. The quality of a robot is measured in terms of accuracy. Quality is related to society loss caused by a robot during its life cycle.

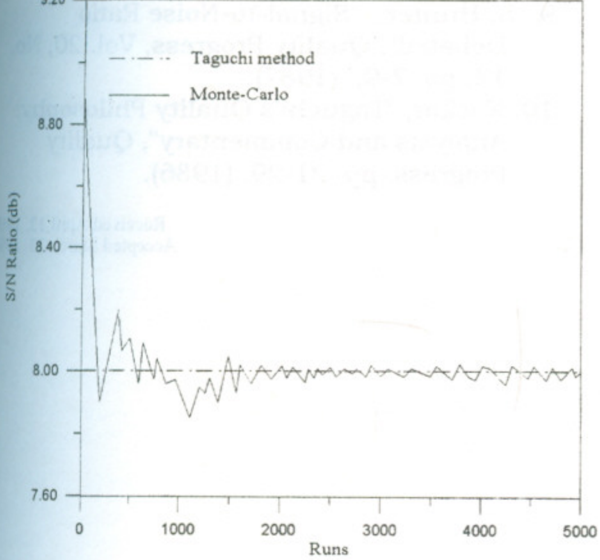

Figure 1 S/N Ratio Comparison

Quality loss function describes the manufacturing cost, operating cost, and development cost of a robot. To minimize the loss, i.e. to maximize the quality, is the strategy of engineering design. The quadratic loss function is the most employed method of quantifying quality loss instead of traditional step function [10].

$$L(y) = ky^{(2)} \tag{6}$$

Where y is the quality characteristic, $L(y)$ is the loss imparted to society and k is the quality loss coefficient.

If the loss caused by exceeding the customer's end-effector deviation tolerance level δ_c is C_c. Consequently, C_c is the customer cost for getting it fixed (by calibration or any other process).

$$k \frac{C_c}{\delta_c^2} \tag{7}$$

Manufacturing tolerances (deviation tolerance) are the limits for shipping the product. Suppose the manufacturer can rework (by calibration or any other process) the robot at a cost of C_m the manufacturer tolerance δ_m can be calculated as

$$\delta_m = \sqrt{\frac{C_m}{k}} \tag{8}$$

The earliest stages of design and development are the areas of greatest cost reduction in products and processes. Quality may be designed into a product or process by making it robust against all noises (manufacturing variations wear and tear, humidity, temperature, dust and variability in human operators).

CONCLUSIONS

This paper presents a tolerance design performance for a PUMA-type manipulator kinematic parameters. Taguchi method has been applied with two and three levels of tolerance ranges. L16 and L32 orthogonal arrays as well as full factorial have been utilized. Taguchi method and Monte-Carlo simulation are compared. The presented methods have shown that interactions and confounding occur when low resolution orthogonal arrays are used. Three-way interaction is less significant than main effects and two-way interaction. Therefore, for fast and complicated design, the three-way interaction could be ignored. An extended Taguchi method is recommended to be used in full-factorial design for the inner array. The effect of the (k-1) joint of a long link (k) on the performance characteristics (accuracy) is significant. Thus, the interaction of that joint with other joints should be considered. Even though the performance measure using Monte-Carlo simulation is more accurate, the extended Taguchi method has shown more computationally efficient. To evaluate the performance characteristic of robot manipulator tolerance design, full factorial two-level-inner array is sufficient.

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مفهوم التصميم الكلى فى جوده الروبوت

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ملخص البحث

تقدم هذه الدراسة نظره جديده و ذلك باعتبار الروبوت كمنتج و أن دقه النهاية الطرفية هى صفه الجودة المميزة للمنتج. الهدف من هذا العمل هو تقليل التغيرات الازاحيه و الدورانيه الحادثه للنهايه الطرفيه ، وقد استخدمت طرق **Taugchi** و **Monte-Carlo** كذلك تم تقديم مفهوم كل من **Inner-array** و **Outer-array**. حيث تم تخليق تشويش باستخدام **Outer-array** كما استخدمت **Signal to noise** لتقييم أداء النهايه الطرفيه.