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Data-Driven Approach to Using Uniform Experimental Design to Optimize System Compensation Parameters for an Auto-Alignment Machine

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ABSTRACT This paper proposes a data-driven approach using uniform experimental design (DAUED) to optimize system compensation parameters for an auto-alignment machine. The proposed DAUED optimizes system compensation parameters by integrating uniform experimental design with the best combination of parameter values and a stepwise ratio. First, system compensation parameters and a 10-level uniform layout (UL) are used to perform alignment experiments. Second, the best result for the 10-level UL experiments is selected and combined with the stepwise ratio for use in computing the experimental range of each parameter for the next 10-level UL experiments. The steps are repeated until the alignment count remains unchanged. Experiments in industrial examples showed that, compared to the conventional industrial design method, the proposed DAUED requires fewer experiments to obtain the system compensation parameters that minimize the alignment count. For example, to achieve a required alignment accuracy to within 5 μm, the DAUED can obtain the best system compensation parameters in only 30 experiments and with an alignment count of 1. In addition, in 30 independent runs using the best compensation parameters, the mean and the standard deviations in alignment counts are 1 and 0, respectively. That is, the best system compensation parameters are robust and stable. In contrast, the industrial design method previously used by engineers requires more than 200 experiments to obtain the system compensation parameters, and its alignment count is as high as 4 or 5. In conclusion, compared to the conventional approach to optimizing system compensation parameters, the proposed DAUED is superior in terms of efficiency (i.e., it requires fewer experiments), effectiveness (i.e., it has a lower alignment count), and robustness (i.e., it achieves a standard deviation of zero in alignment count) in online, real-time, and high-precision optimization of an auto-alignment machine.

INDEX TERMS Precision alignment, system compensation parameters, uniform experimental design.

I. INTRODUCTION

Technology for high precision alignment of cyber-physical systems has been implemented in widely varying domains, including medicine [1]–[3], civil engineering [4], biometrics [5]–[8], traffic control [9], [10], and various industries [11], [12]. Most of the recent technological advances in industrial applications of high precision alignment technology have been in the use of robust intelligence and automation. Among the most important of these improvements is automated vision-servo-based alignment of cyber-physical systems. Because automation has proven effective for solving problems such as labor shortages, high production costs, and high defect rates, researchers and industrial companies are intensively studying ways to increase automation by implementing new technologies such as vision-servo-based alignment. A vision-servo-based alignment system includes an image processing subsystem and a servo motion subsystem [13], [14].

Unit differences between the two subsystems are adjusted by applying system compensation parameters. Increasing the efficiency and accuracy of vision-servo-based alignment systems used in online real-time auto-alignment machines requires improvements in optimization of compensation parameters, motion design, and image processing. Until now, most of the proposed improvements in precision alignment technology have focused on motion design and image processing. To improve stage motion, for example, recent studies have proposed the use of global and micro stage mechanisms [15], high resolution of mechanisms for precision alignment [16], [17], an ultra-low stage to compensate for posture [18], [19], and novel space stage mechanisms [20]. To improve image processing, previous studies have investigated the use of pattern recognition [21], [22], image visual libraries [23], [24], neural networks [25], Kalman filters for estimating centroids of alignment marks [26], [27], and geometric template matching [27], [28].

One problem that has recently emerged in the literature is the optimization of compensation parameters for vision-servo-based alignment systems. Conventional methods of parameter optimization include trial-and-error method, one-factor-at-one-time method, Taguchi method [29], and uniform design method [30]–[32]. However, all of these methods are limited by their reliance on expert knowledge and experience to perform offline processes. Although the Taguchi method is a systematic method, it limits the number of levels for each parameter, it is highly dependent on expert knowledge for determining parameter ranges, and it is unsuitable for online real-time processes. A soft computing technology proposed by Tsai *et al.* [12] integrated a full-factorial experimental design, an artificial neural network, and the Taguchi-based genetic algorithm to optimize the positional compensation parameters for a flexible printed circuit board exposure machine. The method, which has proven to be highly effective for offline processes, uses a full-factorial experimental design to collect data, an artificial neural network to build the positioning model, and Taguchi-based genetic algorithm to optimize parameters. For performing automatic online searches in real time, Tsai *et al.* [11] proposed an intelligent data-driven adaptive method (IDAM) to optimize system integration scaling factors. By combining three-level orthogonal arrays, signal-to-noise ratio, the best combined strategy, and a stepwise ratio, the proposed IDAM achieved higher efficiency in parameter optimization for automatic online real-time machines in comparison with the method proposed earlier in Tsai *et al.* [12]. However, the IDAM performs three-level orthogonal experiments, which limits the resolution and robustness of the best parameters. To address these limitations, this study developed a data-driven approach using uniform experimental design (DAUED). Using the proposed DAUED to optimize system compensation parameters for an auto-alignment machine improves the resolution of each parameter by providing more levels compared to conventional methods.

In addition to increasing the number of levels for each parameter, proposed DAUED also improves IDAM by determining the parameter arrangement that maximizes the uniformity of the layout (UL). The experiments in this study were performed using a DAUED with a ten-level UL of $U_{10}(10^{10})$ rather than using an IDAM with a three-level $L_9(3^4)$. The $U_{10}(10^{10})$ in the DAUED accommodates up to ten parameters, each of which has ten levels. In contrast, the $L_9(3^4)$ in the IDAM only accommodates up to four parameters, each of which has three levels. The use of ten levels in the DAUED provides superior resolution. For fair comparisons, the $U_{10}(10^{10})$ were adopted because the ten experiments in $U_{10}(10^{10})$ equal the nine experiments in $L_9(3^4)$ plus an additional experiment performed according to the inference results. The DAUED can also determine the best parameters in fewer computational steps compared to the IDAM.

In the DAUED proposed in this study, a ten-level UL of $U_{10}(10^{10})$ was integrated with the best combination of parameter values and a stepwise ratio to optimize system compensation parameters for real-time online high precision alignment of an auto-alignment machine. Firstly, the system compensation parameters and the ten-level UL were used to perform the alignment experiments. Secondly, the best result of the ten-level UL experiments was selected and combined with the stepwise ratio to compute the experimental range of each parameter for the next ten-level UL experiments. The steps were repeated until the alignment count remained unchanged. Experiments were also performed to compare the performance of the DAUED when using different stepwise ratios. Examples of practical applications of the DAUED for designing system compensation parameters for real-time online tests of an auto-alignment machine were then evaluated. The experiments showed that the proposed DAUED indeed obtained more robust parameters in fewer experiments compared to the IDAM.

This paper is organized as follows. Section 2 defines the research issue. Section 3 briefly discusses related works. Section 4 introduces the proposed approach. Section 5 presents and discusses the case study results. Finally, Section 6 concludes the study.

II. PROBLEM DESCRIPTION

Figure 1 shows that an auto-alignment system generally comprises an image processing sub-system and a servo motion sub-system. The image processing sub-system grabs and recognizes fiducial marks on the mask and panel and then calculates the differences between the marks. Then, a stage motion sub-system is driven to reach the target.

The auto-alignment system increases the accuracy, the automation, and the speed of the production process. Figure 2 is a flow chart of the alignment procedure. The main steps include image acquisition, image processing, difference compensation, and servo motion. The auto-alignment system

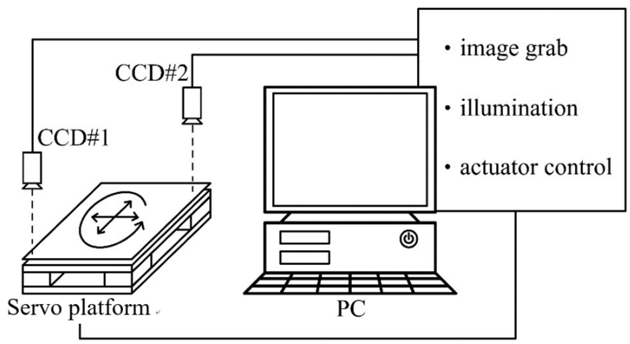

FIGURE 1. Schematic diagram of auto-alignment system.

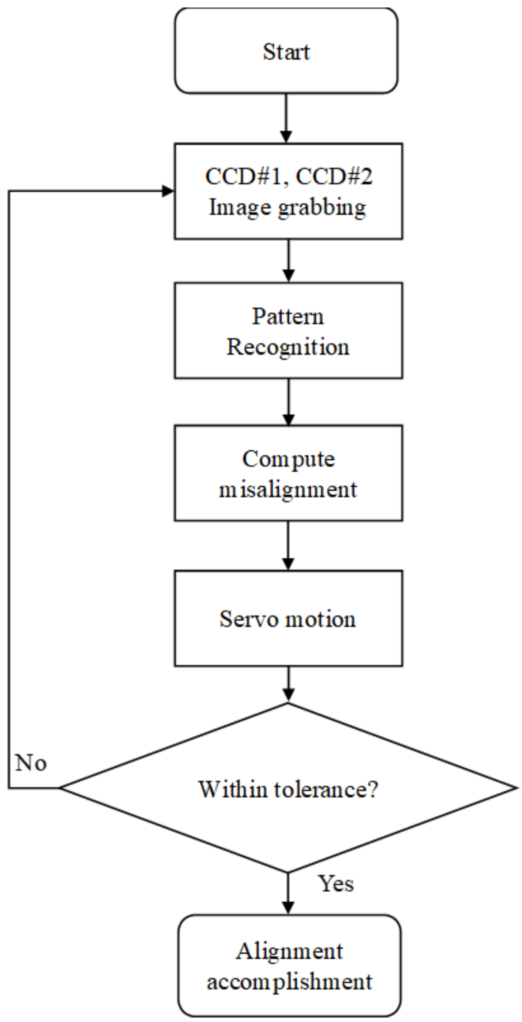

FIGURE 2. Flowchart of alignment process.

determines whether fiducial marks that enter its field of view can be grabbed by the charge-coupled-device (CCD) cameras. The fiducial marks in this system were crosses or circles.

After the system locates the fiducial marks in the grabbed image, it calculates the compensation for the differences between the crosses and circles. The marks in the images

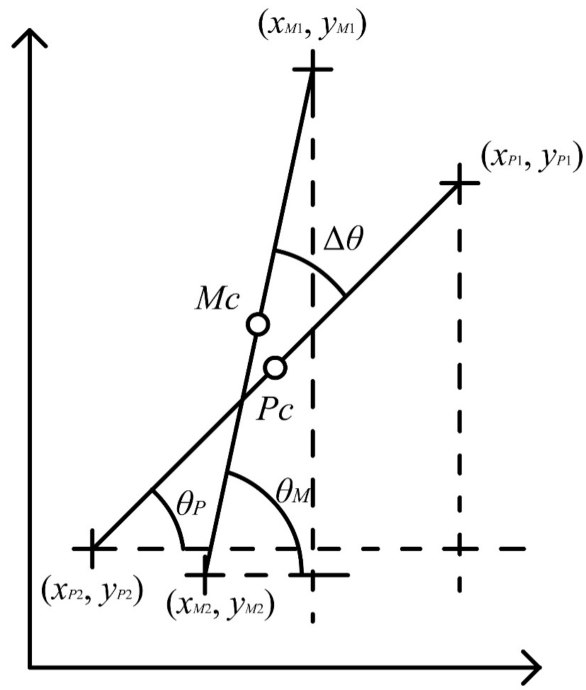

FIGURE 3. Coordinates of alignment marks.

grabbed by the two CCD cameras (CCDs #1 and #2 in Fig. 1) are recognized by the image processing sub-system. Figure 3 shows that the mask coordinates are defined as (x_{M1}, y_{M1}) and (x_{M2}, y_{M2}), and the panel coordinates are defined as (x_{P1}, y_{P1}) and (x_{P2}, y_{P2}). The coordinates of the geometric centers of the mask (Mc) and the panel (Pc) are

$$Mc = \left(\frac{x_{M1} + x_{M2}}{2}, \frac{y_{M1} + y_{M2}}{2}\right), \tag{2.1}$$

and

$$Pc = \left(\frac{x_{P1} + x_{P2}}{2}, \frac{y_{P1} + y_{P2}}{2}\right). \tag{2.2}$$

Therefore, the deviation of Mc and Pc can be described as Δx and Δy, where

$$\Delta x = \frac{x_{M1} - x_{P1} + x_{M2} - x_{P2}}{2}, \tag{2.3}$$

and

$$\Delta y = \frac{y_{M1} - y_{P1} + y_{M2} - y_{P2}}{2}. \tag{2.4}$$

The rotation angles are

$$\theta_{\mathrm{M}} = \tan^{-1}\left(\frac{y_{M2} - y_{M1}}{x_{M2} - x_{M1}}\right), \tag{2.5}$$

and

$$\theta_{\mathrm{P}} = \tan^{-1}\left(\frac{y_{P2} - y_{P1}}{x_{P2} - x_{P1}}\right). \tag{2.6}$$

Thus, deviation between θ_M and θ_P is

$$\Delta\theta = \theta_{\mathrm{M}} - \theta_{\mathrm{P}}, \tag{2.7}$$

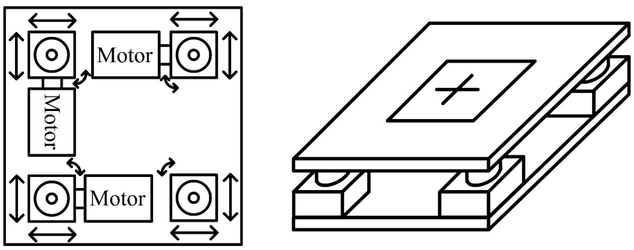

FIGURE 4. **Structure of servo platform for the alignment system.**

Experiment number	Column numbers									
	1	2	3	4	5	6	7	8	9	10
1	1	2	3	4	5	6	7	8	9	10
2	2	4	6	8	10	1	3	5	7	9
3	3	6	9	1	4	7	10	2	5	8
4	4	8	1	5	9	2	6	10	3	7
5	5	10	4	9	3	8	2	7	1	6
6	6	1	7	2	8	3	9	4	10	5
7	7	3	10	6	2	9	5	1	8	4
8	8	5	2	10	7	4	1	9	6	3
9	9	7	5	3	1	10	8	6	4	2
10	10	9	8	7	6	5	4	3	2	1
~~11~~	~~11~~	~~11~~	~~11~~	~~11~~	~~11~~	~~11~~	~~11~~	~~11~~	~~11~~	~~11~~

FIGURE 5. **Construction of ten-level UL of $U_{10}(10^{10})$ by deleting the 11^{th} row of $U_{11}(10^{10})$.**

After the deviations are calculated, the compensation information is sent to the servo motion sub-system, and the servo-platform moves to the target position. Figure 4 shows that the platform architecture comprises the base, work bench, motor, and ball screw. Three actuators with four prismatic-prismatic-revolute joints move the platform. The detailed architecture of the platform was described in Jiang *et al.* [13] and Minaeian *et al.* [14].

Since the deviations (Δx, Δy, and $\Delta\theta$) in the grabbed image differ from the deviations in the servo platform, system compensation parameters p_x, p_y, and p_q, are used to compensate for the different deviations.

III. RELATED WORKS

Uniform experimental design (UED) method developed by Wang and Fang [30], Fang [31], and Tsao and Lee [32] uses space filling designs to construct a set of experimental points uniformly scattered in a continuous design parameter space. The UED only considers uniform dispersion and abandons comparable orderliness. Therefore, the UED minimizes the number of experiments needed to acquire all available information.

The UL is represented by $U_a(a^b)$, where U is the symbol of UL, a is the number of experiments and levels, and b is the number of parameters. The UL is constructed by the good lattice point method. The steps for performing good lattice point method to construct the UL are as follows.

Step 1: Let a be the number of experiments. Find positive integers h that are smaller than a where the greatest common divisor between h and a is 1.

Step 2: Use the following equation to calculate element $u_{i,j}$ of the UL:

$$u_{i,j} = ih_j \quad [\text{mod } a] \tag{3.1}$$

where

$$u_{1,j} = h_j,$$
$$u_{k+1,j} = \begin{cases} u_{k,j} + h_j, & \text{if } u_{k,j} + h_j \le a \\ u_{k,j} + h_j - a & \text{if } u_{k,j} + h_j > a \end{cases}, \quad k, j = 1, \ldots, a-1. \tag{3.2}$$

In the UED method, when a is prime number, the UL has $(a-1)$ columns. When a is not prime number, the UL has less than $(a-1)$ columns. In this case, Wang and Fang [30] suggested removing the last row of the UL to construct the UL. For example, Fig. 5 shows that the ten-level UL of $U_{10}(10^{10})$ is obtained by deleting the last row of the eleven-level UL of $U_{11}(11^{10})$.

TABLE 1. **A ten-level UL of $U_{10}(10^{10})$.**

Experiment number	Column numbers									
	1	2	3	4	5	6	7	8	9	10
1	1	2	3	4	5	6	7	8	9	10
2	2	4	6	8	10	1	3	5	7	9
3	3	6	9	1	4	7	10	2	5	8
4	4	8	1	5	9	2	6	10	3	7
5	5	10	4	9	3	8	2	7	1	6
6	6	1	7	2	8	3	9	4	10	5
7	7	3	10	6	2	9	5	1	8	4
8	8	5	2	10	7	4	1	9	6	3
9	9	7	5	3	1	10	8	6	4	2
10	10	9	8	7	6	5	4	3	2	1

TABLE 2. **The table for selecting column numbers in $U_{10}(10^{10})$.**

Factor number	Column numbers
2	1 7
3	1 5 7
4	1 2 5 7
5	1 2 3 5 7
6	1 2 3 5 7 10

When the number of testing variables is less than that of the selected UL, the factors should be selected. Therefore, each UL has a table that indicates what factors should be chosen for the design variables and what experimental points for design variables can be uniformly distributed in good lattices. The centered L_2-discrepancy (CL_2) is considered an appealing property because it remains invariant when the order of runs is changed and when the factors are relabeled. It reflects the points on any plane that passes through the center of the unit cube and is parallel to one of its faces. The latter is equivalent to the invariance that occurs when the ith coordinate x_i is replaced by $1 - x_i$ for some $i = 1, \ldots, s$. For analyzing CL_2, Hickernell [33] proposed the following mathematical

TABLE 3. The ten-level UL of $U_{10}(10^3)$ for allocation of three design parameters with ten levels.

Experiment number	Design parameters		
	p_x	p_y	p_q
1	1	5	7
2	2	10	3
3	3	4	10
4	4	9	6
5	5	3	2
6	6	8	9
7	7	2	5
8	8	7	1
9	9	1	8
10	10	6	4

expression:

$$CL_2(X) = \left\{ \begin{array}{l} \left(\frac{13}{12}\right)^s - \frac{2}{n}\sum_{k=1}^{n}\prod_{j=1}^{s}\left[1+\frac{1}{2}\left|x_{kj}-\frac{1}{2}\right|-\frac{1}{2}\left|x_{kj}-\frac{1}{2}\right|^2\right] \\ +\frac{1}{n^2}\sum_{k,j=1}^{n}\prod_{i=1}^{s} \\ \times\left[1+\frac{1}{2}\left|x_{ki}-\frac{1}{2}\right|+\frac{1}{2}\left|x_{ji}-\frac{1}{2}\right|-\frac{1}{2}\left|x_{ki}-x_{ji}\right|\right] \end{array} \right\}^{\frac{1}{2}} \tag{3.3}$$

The uniformity of UED is confirmed by CL_2, and the design points of UED are uniformly scattered in the experimental domain. For example, Table 1 shows a ten-level UL of $U_{10}(10^{10})$, and Table 2 is the table used for $U_{10}(10^{10})$. The tables show that the UED is very suitable for solving problems involving multiple factors with multiple levels.

After the UL experiments are completed, regression analysis is performed to analyze the experimental results and the fit relationships between dependent variable Y and independent variables x. Equation 3.4 is the general regression equation used to find the best combination of parameters for the variables:

$$Y = \sigma_0+\sum_{i=1}^{n}\sigma_{i1}x_i+\sum_{i=1}^{n}\sigma_{i2}x_i^2+\cdots+\sum_{i=1}^{n}\sigma_{im}x_i^m + \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\sigma_{ij2}x_ix_j+\varepsilon, \tag{3.4}$$

where σ_0 is a constant; where $\sigma_{i1}, \sigma_{i2}, \ldots, \sigma_{im}, \sigma_{ij2}$ are the respective coefficients for $x_i, x_i^2, \ldots, x_i^m$; where σ_{ij2} is the coefficient for x_ix_j; and where ε is error.

IV. USE OF DAUED TO OPTIMIZE SYSTEM COMPENSATION PARAMETERS FOR AN AUTO-ALIGNMENT MACHINE

In the DAUED method proposed in this study, UED was integrated with the best combination of parameter values and a stepwise ratio to find the system compensation parameters needed for online real-time precision alignment of an auto-alignment machine. First, the system compensation parameters were determined, and the ten-level UL was used to perform alignment experiments. Second, the best result for the ten-level UL experiments was chosen and combined with the stepwise ratio to compute the experimental range of each parameter for next ten-level UL experiments. The steps were repeated until the alignment count remained unchanged.

The detailed steps of the proposed DAUED were as follows.

A. INITIALIZE THE DAUED

The design parameters were the three system compensation parameters (p_x, p_y, and p_q). For each parameter, the range and solution resolution were selected, and the stepwise ratio was set. The ten-level UL of $U_{10}(10^3)$ was used to conduct experiments using the three design parameters, and its performance was compared with that of the three-level $L_9(3^3)$ used in IDAM. The results for the ten experiments performed in the $U_{10}(10^3)$ were compared with the results for the nine experiments in $L_9(3^3)$ and one additional experiment based on the inference results. The experimental output was the alignment count.

B. PERFORM TEN-LEVEL UL OF $U_{10}(10^3)$ EXPERIMENTS FOR ONLINE REAL-TIME PRECISION ALIGNMENT

Table 2 is the table for $U_{10}(10^{10})$. To conduct the experiments, columns 1, 5, and 7 of $U_{10}(10^{10})$ in Table1 were used in $U_{10}(10^3)$ to allocate the three design parameters in the ten levels as shown in Table 3. The operational range for each design parameter was divided into ten levels and entered in the $U_{10}(10^3)$ accordingly. Then, the experiments were performed sequentially, and the alignment counts were recorded.

C. COMPUTE THE OPERATIONAL RANGE OF EACH PARAMETER FOR THE NEXT TEN-LEVEL UL EXPERIMENTS

The best result for the ten-level UL experiments was identified, and its parameter combination and stepwise ratio were used to compute the operational range of each parameter for next ten-level UL experiments. Steps (2) and (3) were repeated until the alignment count remained unchanged.

The following algorithm was used to obtain the ten-level factor values for the new individual. The variables were defined as follows: *var_no* was the variable (factor) number; *lowest* and *highest* were the lowest and highest values for each design variable, respectively; *low* and *upp* were the temporary values for *lowest* and *highest*, respectively; *level* was the level value; *a* was the total number of experiments in the UL; *best_para* was the best parameter obtained by the best results for the UL experiments; and *stepwise_ratio* was a stepwise ratio.

Begin
    For $k = 1$ to *var_no*
        $low \leftarrow lowest(k)$
        $upp \leftarrow highest(k)$
        For $i = 1$ to a
            $level(i, k) \leftarrow low + ((upp - low) / (a - 1) *(i - 1))$
        End

$lowest(k) \leftarrow best\_para(k) - (upp - low) * stepwise\_ratio/2$

$highest(k) \leftarrow best\_para(k) + (upp - low) * stepwise\_ratio/2$

End

End

D. DETAILED STEPS FOR USING DAUED METHOD TO FIND SYSTEM COMPENSATION PARAMETERS

Step 1: Set $j = 1$, where j is the number of experiments. Designate the alignment count as the experimental output value and a stepwise ratio.

Step 2: Generate three sets V_1, V_2, and V_3, each of which has ten-level factor values, and allocate the three sets V_1, V_2, and V_3 into $U_{10}(10^3)$. Use the above algorithms to obtain the ten-level factor values.

Step 3: Calculate the fitness value for the individual of the j^{th} experiment.

Step 4: If $j > a$, where a is the total number of experiments in the the UL, perform Step 5. Otherwise, $j = j+1$, and repeat Steps 3-4.

Step 5: Find the minimal output value from the $U_{10}(10^3)$, and obtain the improved individual vector of the factor values. If the number of improved individual vectors exceeds 2, select the first vector.

Step 6: For the next ten-level UL experiments, use new individuals of the ten-level factor values that were calculated by the improved individual vector obtained in Step 5 with the stepwise ratio.

Step 7: Repeat Steps 2-6 until the alignment count remains unchanged.

Step 8: Display the best system compensation parameter values and its alignment count.

V. INDUSTRIAL IMPLEMENTATION AND RESULTS

The proposed DAUED was used to optimize system compensation parameters for online real-time precision alignment in two industrial examples of auto-alignment machines. One industrial example required positional accuracy to within 3 micrometers, and the other required positional accuracy to within 5 micrometers. The Metal Industries Research and Development Centre (MIRDC) provided the auto-alignment machine for performing experiments and validating experimental results. Figure 6 shows the alignment marks, and Figure 7 is a photograph of the auto-alignment machine used in this experiment. Figure 8 shows the visual human-machine interface for the proposed DAUED.

A. INDUSTRIAL EXAMPLE 1: REQUIRED POSITIONAL ACCURACY TO WITHIN 3 MICROMETERS

The three major system compensation parameters for online real-time precision alignment of the auto-alignment machine were p_x, p_y, and p_q. In the UL experiments, for example, the initial values for factors p_x and p_y ranged from 0.211 to 0.317, and the initial values for factor p_q ranged from 0.475 to 0.581. The range of values for each factor was divided into

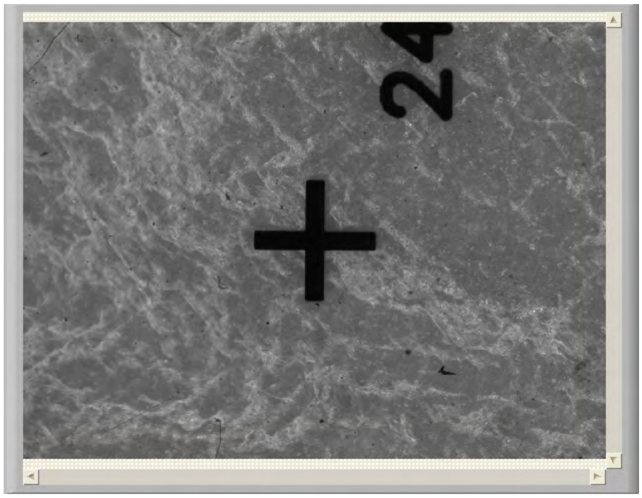

FIGURE 6. Illustration of alignment mark.

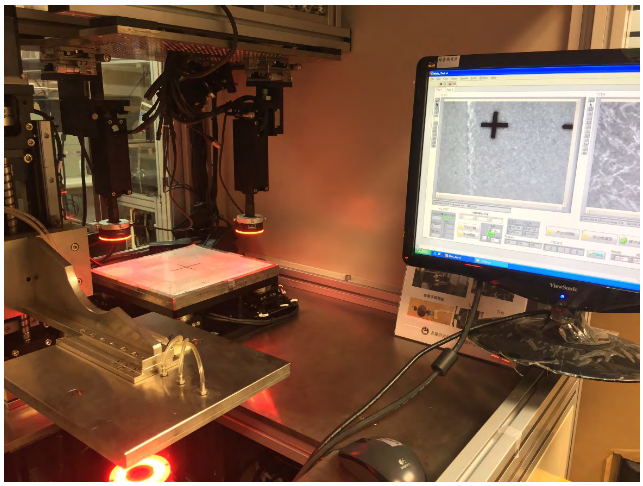

FIGURE 7. Auto-alignment machine.

ten levels that were allocated into the $U_{10}(10^3)$. The ten-level UL of $U_{10}(10^3)$ was used to perform experiments and to depict nonlinear effects. The stepwise ratio was set to 0.9, and the solution accuracy of each factor was set to 10^{-3}. In the experiments performed in industrial example 1, the required positional accuracy of online real-time precision alignment was 3 micrometers.

Table 4 shows the results obtained by the proposed DAUED with the $U_{10}(10^3)$ and the initial ten levels of each factor. The best combination of parameter values in experiment 1 was [0.221, 0.258, and 0.546], which had an alignment count of 2. In experiment 2, the value range for each factor was obtained by the best combination of parameter values in experiment 1 with a stepwise ratio of 0.9. The value ranges in experiment 2 were 0.211 to 0.259 for p_x; 0.211 to 0.306 for p_y, and and 0.498 to 0.581 for p_q. Table 5 shows that the best combination of parameter values in experiment 2 was [0.211, 0.253, 0.553], which had an alignment count of 2. In experiments 1 and 2, the UL experiments were stopped

TABLE 4. Results for experiment 1 using the proposed DAUED with $U_{10}(10^3)$, a stepwise ratio of 0.9, and a required positional accuracy to within 3 micrometers in industrial example 1.

Experiment number	Parameters			Alignment count
	p_x	p_y	p_q	
1	0.211	0.258	0.546	2
2	0.223	0.317	0.499	3
3	0.235	0.246	0.581	3
4	0.246	0.305	0.534	3
5	0.258	0.235	0.487	3
6	0.270	0.293	0.569	3
7	0.282	0.223	0.522	3
8	0.293	0.282	0.475	3
9	0.305	0.211	0.557	4
10	0.317	0.270	0.510	2
Best combination	0.211	0.258	0.546	2

TABLE 5. Results for experiment 2 when using the proposed DAUED with $U_{10}(10^3)$, a stepwise ratio of 0.9, and a required positional accuracy to within 3 micrometers in industrial example 1.

Experiment number	Parameters			Alignment count
	p_x	p_y	p_q	
1	0.211	0.253	0.553	2
2	0.216	0.306	0.517	3
3	0.222	0.243	0.581	3
4	0.227	0.295	0.544	3
5	0.232	0.232	0.507	3
6	0.238	0.285	0.572	2
7	0.243	0.222	0.535	3
8	0.248	0.274	0.498	2
9	0.253	0.211	0.563	4
10	0.259	0.264	0.526	2
Best combination	0.211	0.253	0.553	2

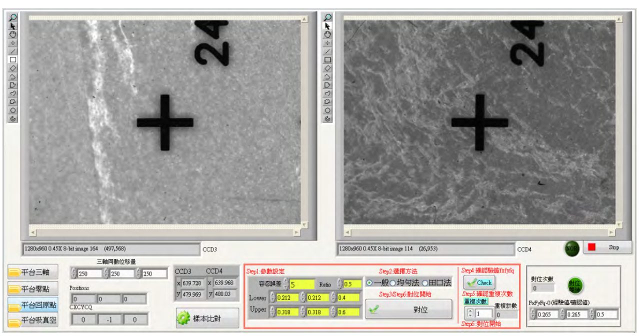

FIGURE 8. Visual human-machine interface for the proposed DAUED method.

when the alignment count remained unchanged. Therefore, for the proposed DAUED, the best combination of the factor values was [0.211, 0.253, 0.553], the lowest alignment count was 2, and the required number of experiments was 20.

Since the proposed DAUED was inspired by the IDAM [11], the performance comparisons used IDAM for experiments in online real-time precision alignment of the same auto-alignment machine. In three-level $L_9(3^4)$ experiments, the front three columns of the $L_9(3^4)$ (as shown in Table 6) for the IDAM were used to accommodate the three system compensation parameters. The initial value range for factors p_x and p_y was 0.211 to 0.317, and the initial value range for factor p_q was 0.475 to 0.581. The stepwise ratio was set to 0.9, and the solution accuracy of each factor was set to 10^{-3}. The value range of each factor was divided into three levels that were allocated into the $L_9(3^4)$. Table 7 shows the three-level L_9 for allocation of three design parameters with three levels and their alignment counts. Table 7 shows that the best combination of parameter values was [0.221, 0.264, and 0.475], which had an alignment count of 3. Table 8 further shows that, in experiment 2, the value range for each factor was obtained by the best combination of parameter

TABLE 6. The front three $L_9(3^4)$ columns used to allocate the three system compensation parameters with three levels in the IDAM.

Experiment number	Design parameters		
	p_x	p_y	p_q
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

TABLE 7. Results for experiment 1 when using the IDAM with L_9, a stepwise ratio of 0.9, and a required positional accuracy to within 3 micrometers in industrial example 1.

Experiment number	Parameters p_x	p_y	p_q	Alignment count	η
1	0.211	0.211	0.475	4	-12.041
2	0.211	0.264	0.528	3	-9.542
3	0.211	0.317	0.581	3	-9.542
4	0.264	0.211	0.528	5	-13.979
5	0.264	0.264	0.581	3	-9.542
6	0.264	0.317	0.475	3	-9.542
7	0.317	0.211	0.581	4	-12.041
8	0.317	0.264	0.475	3	-9.542
9	0.317	0.317	0.528	4	-12.041
E_{11}, E_{21}, E_{31}	-27.604	-38.062	-31.126		
E_{12}, E_{22}, E_{32}	-33.064	-25.105	-32.041		
E_{13}, E_{23}, E_{33}	-33.625	-31.126	-31.126		
Maximum effect	-27.604	-25.105	-31.126		
Inference level	1	2	1		
Best individual	0.211	0.264	0.475	3	

TABLE 8. Results for experiment 2 when using the IDAM with L_9, a stepwise ratio of 0.9, and a required positional accuracy to within 3 micrometers in industrial example 1.

Experiment number	Parameters p_x	p_y	p_q	Alignment count	η
1	0.211	0.216	0.475	4	-12.041
2	0.211	0.264	0.523	2	-6.021
3	0.211	0.312	0.570	3	-9.542
4	0.259	0.216	0.523	4	-12.041
5	0.259	0.264	0.570	2	-6.021
6	0.259	0.312	0.475	3	-9.542
7	0.306	0.216	0.570	5	-13.979
8	0.306	0.264	0.475	3	-9.542
9	0.306	0.312	0.523	4	-12.041
E_{11}, E_{21}, E_{31}	-27.604	-38.062	-31.126		
E_{12}, E_{22}, E_{32}	-27.604	-21.584	-30.103		
E_{13}, E_{23}, E_{33}	-35.563	-31.126	-29.542		
Maximum effect	-27.604	-21.584	-29.542		
Inference level	1	2	3		
Best individual	0.211	0.264	0.570	2	

TABLE 9. Results for experiment 3 when using the IDAM with L_9, a stepwise ratio of 0.9, and a required positional accuracy to within 3 micrometers in industrial example 1.

Experiment number	Parameters p_x	p_y	p_q	Alignment count	η
1	0.211	0.221	0.485	4	-12.041
2	0.211	0.264	0.528	2	-6.021
3	0.211	0.307	0.570	3	-9.542
4	0.254	0.221	0.528	4	-12.041
5	0.254	0.264	0.570	2	-6.021
6	0.254	0.307	0.485	3	-9.542
7	0.297	0.221	0.570	4	-12.041
8	0.297	0.264	0.485	2	-6.021
9	0.297	0.307	0.528	3	-9.542
E_{11}, E_{21}, E_{31}	-27.604	-36.124	-27.604		
E_{12}, E_{22}, E_{32}	-27.604	-18.062	-27.604		
E_{13}, E_{23}, E_{33}	-27.604	-28.627	-27.604		
Maximum effect	-27.604	-18.062	-27.604		
Inference level	1	2	1		
Best individual	0.211	0.264	0.485	2	

values in experiment 1 with a stepwise ratio of 0.9. The value ranges in experiment 2 were [0.211, 0.259, 0.306] for p_x, [0.216, 0.264, 0.312] for p_y, and [0.475, 0.523, 0.570] for p_q. The best combination of parameter values in experiment 2 was [0.211, 0.264, 0.570], which had an alignment count of 2. Table 9 shows the results for experiment 3. The value

TABLE 10. Results in terms of the lowest alignment count and (experimental runs for the lowest alignment count) in online real-time implementation of industrial application 1 using the DAUED with different solution spaces and different stepwise ratios.

Solution space	Stepwise ratios				
	0.5	0.6	0.7	0.8	0.9
p_x [0.211, 0.317] p_y [0.211, 0.317] p_q [0.475, 0.581]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)
p_x [0.184, 0.344] p_y [0.184, 0.344] p_q [0.448, 0.608]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)
p_x [0.158, 0.370] p_y [0.158, 0.370] p_q [0.422, 0.634]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)
p_x [0.131, 0.397] p_y [0.131, 0.397] p_q [0.395, 0.661]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)

TABLE 11. Results in terms of the lowest alignment count and (experimental runs when the lowest alignment count appears) in online real-time implementation of industrial application 1 using the IDAM with different solution spaces and different stepwise ratios.

Solution space	Stepwise ratios				
	0.5	0.6	0.7	0.8	0.9
p_x [0.211, 0.317] p_y [0.211, 0.317] p_q [0.475, 0.581]	2 (20)	2 (20)	2 (20)	2 (20)	2 (30)
p_x [0.184, 0.344] p_y [0.184, 0.344] p_q [0.448, 0.608]	2 (30)	2 (20)	2 (20)	2 (20)	2 (20)
p_x [0.158, 0.370] p_y [0.158, 0.370] p_q [0.422, 0.634]	2 (30)	2 (30)	2 (30)	2 (40)	2 (30)
p_x [0.131, 0.397] p_y [0.131, 0.397] p_q [0.395, 0.661]	2 (30)	2 (30)	2 (40)	2 (40)	2 (40)

range for each factor was obtained by the best combination of parameter values in experiment 2 with a stepwise ratio of 0.9. The value ranges in experiment 3 were [0.211, 0.254, 0.297] for p_x, [0.221, 0.264, 0.307] for p_y, and [0.485, 0.528, 0.570] for p_q. The best combination of parameter values in experiment 3 was [0.211, 0.264, 0.485], which had an alignment count of 2. The three-level L_9 experiments were stopped when the alignment count remained unchanged in experiments 2 and 3. Therefore, the best combination of factor values obtained by the IDAM was [0.211, 0.264, 0.485], the lowest alignment count was 2, and the required number of experiments was 30.

Different stepwise ratios were then compared in terms of alignment count and experimental runs. Stepwise ratios were set to 0.5, 0.6, 0.7, 0.8, and 0.9. Table 10 shows the lowest alignment count and the lowest required number of experiments in an online real-time implementation of the proposed DAUED with $U_{10}(10^3)$ and different stepwise ratios. To find the best parameter combination for various stepwise ratios, the lowest alignment count was 2, and the lowest required number of experiments was 20. That is, the stepwise ratio did not affect the alignment results obtained by the proposed DAUED. Table 11 shows the results in terms of the minimum alignment count and the minimum required number of experiments obtained in an online real-time implementation of the IDAM with the three-level L_9 and various stepwise ratios. The lowest alignment count that obtained the best parameter combination was still 2. However, as the ranges for solution spaces and stepwise ratios increased, the minimum number of experiments needed to obtain the best parameter combination for the lowest alignment count of 2 increased. Therefore, the proposed DAUED is superior to the IDAM in terms of the minimum number of experimental runs needed to obtain the best parameter combination. Table 12 further compares the performance of the DAUED, IDAM, and the previous industrial design method in terms of maximum experimental runs, average alignment count, standard deviation in alignment count obtained in 30 independent experimental runs, and multiple of efficiency improvement (required positional accuracy to within 3 micrometers). The DAUED obtained an average alignment count of 2. The multiple of efficiency improvement was 2.15, which is higher than that of the previous industrial design method. In 30 independent experimental runs, the standard deviation in alignment count was 0. The average alignment count obtained by the IDAM was still superior to the previous industrial design method, but its standard deviation in alignment count exceeded that of DAUED. Therefore, the proposed DAUED outperformed both IDAM and the previous industrial design method it terms of robustness, required number of experimental runs, and efficiency in automatic real-time optimization of system compensation parameters for online alignment systems.

B. INDUSTRIAL EXAMPLE 2: REQUIRED POSITIONAL ACCURACY TO WITHIN 5 MICROMETERS

Three important system compensation parameters for online real-time precision alignment of an auto-alignment machine are p_x, p_y, and p_q. In the UL experiments, for example, the initial values for factors p_x and p_y ranged from 0.158 to 0.370, and the initial values for factor p_q ranged from 0.422 to 0.634. The value range of each factor was divided into ten levels that were allocated into the $U_{10}(10^3)$. The ten-level UL of $U_{10}(10^3)$ was used to perform experiments and to analyze nonlinear effects. The stepwise ratio was set to 0.5, and the solution accuracy of each factor was set to 10^{-3}. In the industrial example, the objective of the experiments was to achieve a positional accuracy to within 5 micrometers for online real-time precision alignment. Table 13 shows the results for experiment 1 using the proposed DAUED with the $U_{10}(10^3)$ and the initial ten levels of each factor. The best combination of parameter values was [0.370, 0.276, and 0.493], which had an alignment count of 2. In experiment 2, the value range for each factor was obtained by the best combination of parameter values in experiment 1 with a stepwise ratio of 0.5. The value ranges in experiment 2 were [0.317 to 0.370] for p_x, [0.223 to 0.329] for p_y, and [0.440 to 0.546] for p_q. Table 14 shows that the best combination of parameter values in the first experiment was [0.317, 0.270, 0.511],

TABLE 12. Performance comparison of DAUED, IDAM, and previous industrial design method in terms of maximum experimental runs, average alignment count (standard deviation) in 30 independent experimental runs, and multiple of efficiency improvement (required positional accuracy to within 3 micrometers).

Method	Maximum experimental runs	Average alignment count (standard deviation)	Multiple of efficiency improvement
DAUED	20	2 (0)	2.15
IDAM	40	2.1 (0.305)	2.05
Previous industrial design method	> 200	4.3 (0.466)	-

TABLE 13. Results for experiment 1 when using the proposed DAUED with $U_{10}(10^3)$, a stepwise ratio of 0.5, and a required positional accuracy to within 5 micrometers in industrial example 2.

Experiment number	Parameters			Alignment count
	p_x	p_y	p_q	
1	0.158	0.252	0.563	3
2	0.182	0.370	0.469	4
3	0.205	0.229	0.634	3
4	0.229	0.346	0.540	4
5	0.252	0.205	0.446	4
6	0.276	0.323	0.610	3
7	0.299	0.182	0.516	6
8	0.323	0.299	0.422	3
9	0.346	0.158	0.587	11
10	0.370	0.276	0.493	2
Best combination	0.370	0.276	0.493	2

TABLE 14. Results for experiment 2 when using the proposed DAUED with $U_{10}(10^3)$, a stepwise ratio of 0.5, and a required positional accuracy to within 5 micrometers in industrial example 2.

Experiment number	Parameters			Alignment count
	p_x	p_y	p_q	
1	0.317	0.270	0.511	2
2	0.323	0.329	0.464	3
3	0.329	0.258	0.546	2
4	0.335	0.317	0.499	3
5	0.341	0.247	0.452	3
6	0.346	0.305	0.534	3
7	0.352	0.235	0.487	3
8	0.358	0.294	0.440	3
9	0.364	0.223	0.522	3
10	0.370	0.282	0.475	2
Best combination	0.317	0.270	0.511	2

which had an alignment count of 2. The UL experiments were stopped when the alignment count remained unchanged in experiments 1 and 2. Therefore, for the proposed DAUED, the best combination of factor values was [0.317, 0.270, 0.511], the lowest alignment count was 2, and the required number of experiments was 20.

The IDAM was used for experiments in online real-time precision alignment of the same auto-alignment machine. In experiments performed using the three-level $L_9(3^4)$, the front three columns of $L_9(3^4)$ (Table 6) of the IDAM were used to accommodate the three system compensation parameters. For example, the initial value range for factors p_x and p_y was from 0.158 to 0.370, and the initial value range for factor p_q was from 0.422 to 0.634. The stepwise ratio was set to 0.5, and the solution accuracy of each factor was set to 10^{-3}. The value range of each factor was divided into three levels that were allocated into the $L_9(3^4)$. Table 15 shows the three-level L_9 for allocation of three design parameters with three levels and their alignment counts. Table 15 shows that the best combination of parameter values was [0.158, 0.264, and 0.528], which had an alignment count of 2. Table 16 shows that, in experiment 2, the value range for each factor was obtained by the best combination of parameter values in experiment 1 with a stepwise ratio of 0.5. The value ranges in experiment 2 were [0.158, 0.211, 0.264] for p_x, [0.211, 0.264, 0.317] for p_y, and [0.475, 0.528, 0.581] for p_q. The best combination obtained in experiment 2 was [0.158, 0.264, 0.475], which had an alignment count of 3. In experiment 3, Table 17 shows the value range for each factor obtained by the best combination of parameter values

TABLE 15. Results for experiment 1 when using IDAM with L_9, a stepwise ratio of 0.5, and a required positional accuracy to within 5 micrometers in industrial example 2.

Experiment number	Parameters			Alignment count	η
	p_x	p_y	p_q		
1	0.158	0.158	0.422	11	-20.828
2	0.158	0.264	0.528	2	-6.021
3	0.158	0.370	0.634	4	-12.041
4	0.264	0.158	0.528	12	-21.584
5	0.264	0.264	0.634	3	-9.542
6	0.264	0.370	0.422	4	-12.041
7	0.370	0.158	0.634	11	-20.828
8	0.370	0.264	0.422	3	-9.542
9	0.370	0.370	0.528	4	-12.041
E_{11}, E_{21}, E_{31}	-38.890	-63.239	-42.411		
E_{12}, E_{22}, E_{32}	-43.167	-25.105	-39.645		
E_{13}, E_{23}, E_{33}	-42.411	-36.124	-42.411		
Maximum effect	-38.890	-25.105	-39.645		
Inference level	1	2	2		
Best individual	0.158	0.264	0.528	2	

TABLE 16. Results for experiment 2 when using IDAM with L_9, a stepwise ratio of 0.5, and a required positional accuracy to within 5 micrometers in industrial example 1.

Experiment number	Parameters			Alignment count	η
	p_x	p_y	p_q		
1	0.158	0.211	0.475	4	-12.041
2	0.158	0.264	0.528	2	-6.021
3	0.158	0.317	0.581	3	-9.542
4	0.211	0.211	0.528	4	-12.041
5	0.211	0.264	0.581	3	-9.542
6	0.211	0.317	0.475	3	-9.542
7	0.264	0.211	0.581	4	-12.041
8	0.264	0.264	0.475	2	-6.021
9	0.264	0.317	0.528	3	-9.542
E_{11}, E_{21}, E_{31}	-27.604	-36.124	-27.604		
E_{12}, E_{22}, E_{32}	-31.126	-21.584	-27.604		
E_{13}, E_{23}, E_{33}	-27.604	-28.627	-31.126		
Maximum effect	-27.604	-21.584	-27.604		
Inference level	1	2	1		
Best individual	0.158	0.264	0.475	3	

TABLE 17. Results for experiment 3 when using IDAM with L_9, a stepwise ratio of 0.5, and a required positional accuracy to within 5 micrometers in industrial example 1.

Experiment number	Parameters			Alignment count	η
	p_x	p_y	p_q		
1	0.158	0.238	0.475	3	-9.542
2	0.158	0.264	0.502	3	-9.542
3	0.158	0.291	0.528	3	-9.542
4	0.185	0.238	0.502	3	-9.542
5	0.185	0.264	0.528	2	-6.021
6	0.185	0.291	0.475	2	-6.021
7	0.211	0.238	0.528	2	-6.021
8	0.211	0.264	0.475	2	-6.021
9	0.211	0.291	0.502	3	-9.542
E_{11}, E_{21}, E_{31}	-28.627	-25.105	-21.584		
E_{12}, E_{22}, E_{32}	-21.584	-21.584	-28.627		
E_{13}, E_{23}, E_{33}	-21.584	-25.105	-21.584		
Maximum effect	-21.584	-21.584	-21.584		
Inference level	2	2	1		
Best individual	0.185	0.264	0.475	2	

in experiment 2 with a stepwise ratio of 0.5. The value ranges in experiment 3 were [0.158, 0.185, 0.211] for p_x, [0.238, 0.264, 0.291] for p_y, and [0.475, 0.502, 0.528] for p_q. The best combination of parameter values in experiment 3 was [0.185, 0.264, 0.475], which had an alignment count of 2. In experiment 4, Table 18 shows that the value range for each factor was obtained by applying the best combination of parameter values in experiment 3 with a stepwise ratio of 0.5. The value ranges in experiment 4 were [0.172, 0.185, 0.198] for p_x, [0.251, 0.264, 0.277] for p_y, and [0.475, 0.489, 0.502] for p_q. The best combination of parameter values in experiment 4 was [0.185, 0.251, 0.475], which had an alignment count

TABLE 18. Results for experiment 4 when using IDAM with L_9, a stepwise ratio of 0.5, and a required positional accuracy to within 5 micrometers in industrial example 1.

Experiment number	Parameters			Alignment count	η
	p_x	p_y	p_q		
1	0.172	0.251	0.475	2	-6.021
2	0.172	0.264	0.489	3	-9.542
3	0.172	0.277	0.502	2	-6.021
4	0.185	0.251	0.489	2	-6.021
5	0.185	0.264	0.502	2	-6.021
6	0.185	0.277	0.475	2	-6.021
7	0.198	0.251	0.502	2	-6.021
8	0.198	0.264	0.475	2	-6.021
9	0.198	0.277	0.489	2	-6.021
E_{11}, E_{21}, E_{31}	-21.584	-18.062	-18.062		
E_{12}, E_{22}, E_{32}	-18.062	-21.584	-21.584		
E_{13}, E_{23}, E_{33}	-18.062	-18.062	-18.062		
Maximum effect	-18.062	-18.062	-18.062		
Inference level	2	1	1		
Best individual	0.185	0.251	0.475	2	

TABLE 19. Lowest alignment count and (experimental runs for the lowest alignment count) in online real-time implementation of industrial application 2 when using the DAUED with different solution spaces and different stepwise ratios.

Solution space	Stepwise ratios				
	0.5	0.6	0.7	0.8	0.9
f_x [0.211, 0.317] f_y [0.211, 0.317] f_q [0.475, 0.581]	2 (20)	2 (20)	2 (20)	2 (20)	1 (30)
f_x [0.184, 0.344] f_y [0.184, 0.344] f_q [0.448, 0.608]	2 (20)	2 (20)	2 (20)	2 (20)	1 (30)
f_x [0.158, 0.370] f_y [0.158, 0.370] f_q [0.422, 0.634]	2 (20)	2 (20)	2 (20)	2 (20)	1 (30)
f_x [0.131, 0.397] f_y [0.131, 0.397] f_q [0.395, 0.661]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)

TABLE 20. Lowest alignment count and (experimental runs for the lowest alignment count) in online real-time implementation of industrial application 2 when using the IDAM with different solution spaces and different stepwise ratios.

Solution space	Stepwise ratios				
	0.5	0.6	0.7	0.8	0.9
f_x [0.211, 0.317] f_y [0.211, 0.317] f_q [0.475, 0.581]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)
f_x [0.184, 0.344] f_y [0.184, 0.344] f_q [0.448, 0.608]	2 (20)	2 (20)	2 (20)	2 (20)	2 (20)
f_x [0.158, 0.370] f_y [0.158, 0.370] f_q [0.422, 0.634]	2 (40)	2 (40)	2 (30)	2 (30)	2 (30)
f_x [0.131, 0.397] f_y [0.131, 0.397] f_q [0.395, 0.661]	2 (40)	2 (40)	2 (30)	2 (30)	2 (40)

of 2. The three-level L_9 experiments were stopped because the alignment count remained unchanged in experiments 3 and 4. Therefore, for the IDAM, the best combination of factor values was [0.185, 0.251, 0.475], the lowest alignment count was 2, and the required number of experiments was 40.

To compare the effects of different stepwise ratios in terms of alignment count and experimental runs, the stepwise ratios were set to 0.5, 0.6, 0.7, 0.8, and 0.9. Table 19 shows the results in terms of the lowest alignment count and the required number of experiments in an online real-time implementation of the proposed DAUED with $U_{10}(10^3)$ and different stepwise ratios. In comparisons of different stepwise ratios used to find the best parameter combination, the lowest alignment count was 1, and the required number of experiments was 30. Additionally, the use of different stepwise ratios in the proposed DAUED did not affect the alignment results except the alignment count was 1 and the required number of experiments was 30. Table 20 shows the results in terms of the lowest alignment count and the required number of experiments in an online real-time implementation of the IDAM with three-level L_9 and different stepwise ratios. The lowest alignment count required to find the best parameter combination was still 2. However, as the ranges for solution spaces and stepwise ratios increased, the required number of experiments needed to obtain the best parameter combination for the lowest alignment count of 2 increased. Therefore, the proposed DAUED is superior to the IDAM in terms of the minimum number of experimental runs needed to obtain the best parameter combination. In Table 21, the DAUED, IDAM, and previous industrial design method are compared in terms of maximum experimental runs, average alignment count, and standard deviation in alignment count in 30 independent experimental runs, and multiple of efficiency improvement (required positional accuracy to within 5 micrometers). The average alignment count obtained by the DAUED was 1, which is higher multiple of efficiency improvement (4.567) compared to the previous industrial design method, and the standard deviation in alignment count was 0 in 30 independent experimental runs. In terms of average alignment count, the IDAM still outperformed the previous industrial design method. However, the IDAM had a larger standard deviation in alignment count compared to DAUED. Therefore, the proposed DAUED was superior to IDAM and the previous

TABLE 21. Performance comparison of DAUED, IDAM, and previous industrial design method in terms of maximum experimental runs, average alignment count (standard deviation) in 30 independent experimental runs, and multiple of efficiency improvement (required positional accuracy to within 5 micrometers).

Method	Maximum experimental runs	Average alignment count (standard deviation)	Multiple of efficiency improvement
DAUED	30	1 (0)	4.567
IDAM	40	2.17(0.379)	2.1
Previous industrial design method	> 200	4.567 (0.868)	-

industrial design method in terms of robustness, required number of experimental runs, and efficiency improvement for automatically finding system compensation parameters for online alignment systems in real time.

Remark: In terms of automatically finding system compensation parameters, the experiments in this study showed that the proposed DAUED outperformed the IDAM in in terms of robustness, experimental runs, and efficiency improvement. The main reason is that the DAUED performed experiments using a ten-level UL of $U_{10}(10^3)$ whereas the IDAM performed experiments using a three-level L_9. The $U_{10}(10^3)$ in the DAUED had ten levels for each parameter while the L_9 in the IDAM had only three levels for each parameter. Therefore, the DAUED provided relatively higher resolution for each parameter. Additionally, according to the computational steps in the experimental processes of the $U_{10}(10^3)$ and the L_9, the best parameter combination was selected directly from the experimental results for $U_{10}(10^3)$. In contrast, the three-level L_9 selected the best parameter combination by applying the inference rule of the Taguchi method. Therefore, the proposed DAUED requires fewer computational steps to find the best system compensation parameters compared to the IDAM.

VI. CONCLUSIONS

By integrating UED with the best parameter combination and stepwise ratio, the proposed DAUED systematically and automatically obtains robust system compensation parameters that minimize the alignment count. The main contribution of this study is the development of the DAUED for rapidly obtaining effective and robust parameters for an online real-time auto-alignment system. Practical industrial applications of the DAUED showed that it requires fewer experiments to obtain the system compensation parameters that minimize the alignment count compared to the IDAM proposed by Tsai *et al.* [11]. The DAUED also obtained smaller mean and standard deviations for the best parameter combination in 30 independent runs. Experiments performed in actual industrial applications confirmed that the system compensation parameters obtained by the DAUED are effective and robust. Therefore, we conclude that the proposed DAUED increases both the effectiveness and speed of automatic searches for better system compensation parameters for auto-alignment machines. Notably, the effective of the DAUED for optimizing system compensation parameters has also been confirmed by practical industrial applications by MIRDC and by Taiwan manufacturers that use auto-alignment machines.

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