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Optimizing Adjustable Parameters of Servo Controller by Using UniNeuro-HUDGA for Laser-Auto-Focus-Based Tracking System

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ABSTRACT This paper aims to minimize the tracking error of a laser auto-focus system that in developing treatment, due to uncertainty setting and modeling of its control system. The error is derived from the imperfect response to the standardized object reference. Optimizing procedure is obtained via multi-variable parameters by using a UniNeuro-hybrid uniform design genetic algorithm (HUDGA). In general, the parameter setting of a servo-controller is determined by some complex analysis or the trial-and-error of an expert person; when the controlled model is distinctly undefined, the process requires considerable time. The UniNeuro-HUDGA requires only 40 experiments to be conducted in the uniform design (UD) of building the metamodel via a neural network (UniNeuro), which is used as the fitness function in the optimization procedure by combining a genetic algorithm with UD. UD is then embedded in the HUDGA for initializing and enriching the solution set, whereas chromosomes used in crossover and mutations generated by UD chromosomes are individually conveyed using a selection procedure combined with the Euclidean distance; then, the optimized setting has investigated by the equipment. This paper concludes that the proposed algorithm optimizes the adjustable parameters of a servo-controller and outperforms the trial-and-error of an expert person.

INDEX TERMS Laser auto focus, tracking system, multi-variable parameters, uniform design, UniNeuro-HUDGA.

I. INTRODUCTION

Laser distance sensors (LDSs) are widely used for observing objects in a prerequisite noncontact design. Thus, with high precision, they detect the position changes of an object without making contact with it; hence, the object is not distorted and the motion target is not dampened. An LDS can be used in various applications such as dimensional measurement, flatness and alignment gauging, welding thickness and run-out controllers, displacement controllers, and 3D scanners. In addition, for specific utilisation, the use of an LDS is crucial in adhesive bead inspection, profiling procedures, structural dynamic controllers, and product inventory [1].

LDS performance is strongly influenced by the movements of the laser in scanning objects, as well as the strength of the laser itself. In a static position, any type of has a specific area related to distance terms. An LDS is influenced by the specifications of the laser generator and the sensor. When the laser moves to detect a product, the necessary control mechanisms that affect the performance of the laser scanner are required. If the LDS is applied as a scanner, it can detect objects in a wider field of view than other sensors can, and its scanning capability enables measuring the size of objects [2]. The scanning performance depends on the number of points that it captures on an object; however, severe problems ensue if the object is not sufficiently smooth or if the multi-reflection area is on the edge [3].

Regarding the aforementioned advances, LDSs have becomes a frequently used device in laboratories and various industries; hence, various studies have been developed technologies to improve the performance of LDS equipment. Previous studies have focused on improving LDS applications such as analysing mechanisms, repairing turbo machinery processes, and detecting the failure of propellers by using laser metal deposition. To demonstrate its performance, LDS usage is twofold: in 3D scanners to detect failures, and for guiding laser metal deposition to fill the involved target [4].

In grinding procedures, LDSs are used for improving the efficiency and accuracy of profiling processes. Using a 3D scanning technique on the basis of combining orthogonal fringe projection with a general analytical description enables evaluating the various parameters and steps involved in the proposed approach [5]. In metal forming, LDSs are used quality control, by providing a comprehensive closed-loop feedback control to ensure flexible metal forming. Additional developments are anticipated in this area through assessing in-place building blocks (actuators, sensors, and models) that can be deployed in future closed-loop control systems in CNC metal forming [6].

LDSs have been applied in the microelectromechanical systems (MEMS) field. Holmstrom *et al.* [7] investigated the requirements of MEMS laser scanners for demanding display applications, as well as the advantages and disadvantages of electrostatic, electromagnetic, piezoelectric, and mechanically coupled actuation principles. Moreover, LDSs have been applied in large-scale capturing for obtaining the 3D point cloud of a moving object by applying motion correction, such that the point cloud is correct both relatively and absolutely. In addition, the true shape of a scanned object can be determined using GPS for detecting a ship's position in a harbour [8]. Other studies have focused on methods and processes for abstracting key points of construction from a 3D laser's data. Based on measurements of the point cloud of a 3D laser scanner, a contour model was constructed in a previous study by using SketchUp software, which enables effective exploration of 3D laser scanning applications in reconstructing 3D city buildings, thereby reducing the workforce and budget for analysing building reconstruction [9].

Other studies have focused on improving LDS performance, such as by designing a new measurement station for a 3D scanner; the station can provide 2D measurement information, including the azimuth, by using the rotary-laser scanning technique. A study concluded that the stability of the rotary-laser scanning technique is affected only by the difference between the two scanning angles [10]. Sun and Li [11] investigated a rapid method for detecting aero-engine blade profile, according to the characteristics of an aero-engine blade surface. This method first deduces an inclination error model in free-form surface measurements based on the non-contact laser triangulation principle [11].

Wang and Feng [3] characterised the scanning orientation effect on the outlier formation for facilitating the development of an effective outlier detection and removal method; inaccurate measurements are affected by an object's edge of reflection. Laser power and scanning velocity influence the morphological evolution of 2D periodic structures in air and water. Femtosecond lasers were applied in determining the properties of material; hydrofluoric acid was then used to remove any oxygen or laser-induced defects from all-silicon structures [12]. An active technique was then employed using an LDS, which projects a sheet of light or a bundle of rays for measuring the distance from the reflected signals through triangulation. Structure-from-motion was then adopted to acquire sequences of 2D photographs passively for recovering 3D information by using photogrammetry techniques and the 3D modelling used in the robotic field [13].

The LDS method for determining the real-time data fusion between monocular vision and a 3D laser scanner can be improved by employing an extrinsic self-calibration measurement; the extrinsic parameters can be obtained automatically by matching the corner features extracted from both vision and the laser data, thus representing a novel calibration method for data fusion. A study developed a data-driven model of laser intensity and investigated its use for simultaneous localisation and mapping in the field of robotics, by modelling the influence of the extrinsic intensity parameters to acquire a pose-invariant measure of surface reflectivity [14]. Furthermore, high-level sensor fusion was applied for object matching between the sensors of a laser scanner and stereo vision. Time synchronisation, the object age, and reordering algorithms were designed for robust tracking of objects. For obtaining an accurate result, a time-delay update algorithm was developed to determine the process time delay of a laser scanner [2].

The previous researchers in gluing and coating systems were using touching sensor for verifying the quality [15], [16]. Distinct from the previous research, in this study, an LDS is used as a laser auto focus system (LAFS); which is controlled by a commercial servo-controller with adjustable parameters. The servo controller was utilized to control the laser's focus target to the fixed distance with the object in fixed z-axis. However, the controller model was unknown; therefore, answering these condition 30 experiments being training data, and then 10 experiments used for testing data by uniform design for forming the meta model by using a neural network (NN),-UniNeuro. After the model formed, it was used as the fitness function for optimization by using the hybrid uniform design genetic algorithm (HUDGA). Finally, after the optimized solution is confirmed, the setting was applied into the device. Traditionally, input parameter values are set by an expert or tuned through time-consuming trial-and-error repetition and intuition.

The remainder of this paper is organised as follows: Chapter 2 discusses the scope of the problem. The proposed method is completely described in Chapter 3, and the results and discussion are presented in Chapter 4. Finally, a conclusion is provided in Chapter 5, and then references are listed in a bibliography.

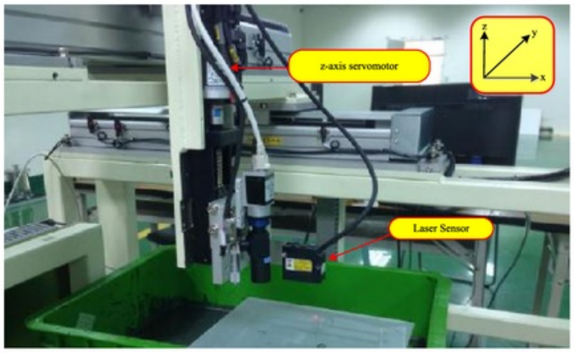

FIGURE 1. Laser auto focus system.

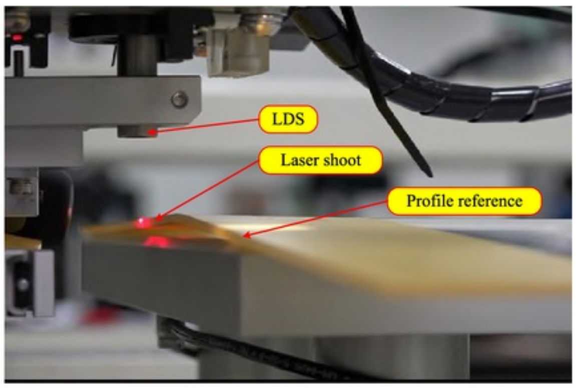

FIGURE 2. LAFS in auto-tracking processing along the profile.

II. PROBLEM DEFINITION

LAFS considered in this study is shown in Fig. 1 and mainly consisted of a laser sensor and three axes servo motion systems. Factually, LAFS is used for auto-tracking the profile of gluing material process, so then the gluing has uniformly thickness that shown in Fig. 2. A servo motion system (z-axis) drives the laser sensor in the area while the laser reflects the object to a complementary metal–oxide–semiconductor detector; feedback is then delivered to a servo controller of z-axis to evaluate and synchronic for the next shoot. All the mechanisms are controlled by a programmable logic controller (PLC), and the adjustable-parameter inputs and measured result output are displayed on a monitor. Originally, there are three axes movements can be operated in this system; wherein each axis leaded by a controller unit coupled with its encoder that used to maintain the performance of LAFS. The whole control structure of LAFS is shown in Fig. 3.

This study focuses for optimizing the adjustable parameters of z-axis servo controller for settling the z-axis distance between laser sensor and object during constant y-axis moves while scanning profile process; then affected by the feedback response of z-axis servomotor used for capturing the object's profile. In order to improve LAFS's performance, the profile reference is defined for judging its achievement via minimizing the tracking error.

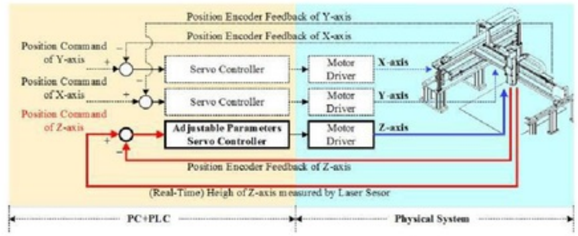

FIGURE 3. LAFS with its servo controller unit mechanism.

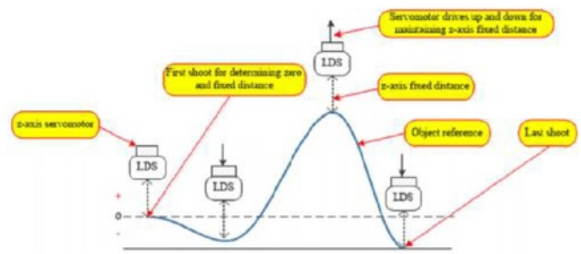

FIGURE 4. Maintaining the z-axis distance by servomotor.

Fig. 4 shows the LAFS mechanism, which LDS moves in y-axis 200m/s constantly for scanning the profile reference during its travel. Simultaneously, the servomotor of z-axis drives the LDS for maintaining the position with the fixed distance with the object. The fixed distance is denote when in the first shoot, so then this distance used as reference for servo controlling that leads by adjustable-parameters for controlling the servomotor movement as response of z-axis distance changes due to the profile touched. The moves of y-axis coupled with z-axis motion together are used for detecting the profile of object that shown in numerical distance on the screen, while adjustable-parameter values have set manually to perform to reduce the tracking error. Therefore, UniNeuro-HUDGA is proposed in this study to determine and then optimize the values of adjustable parameters with a few numbers of experiments.

In this study, an LAFS was integrated with a servo controller by regulating the adjustable parameters, (K_A,K_B, and K_C), to control the z-axis distance; the suitable response of the z-axis servomotor affected by the scanner moving speed in y-axis distance also the contour of object. Fig. 4 shows the servo control system of z-axis. Thus, the optimization is needed to adjust the distance of laser source and the object in z-axis fixed by references distance that determined at the first point/ first shoot on object. The z-axis distance maintains in the fixed distance, while the laser sensor moves continuously in the y-axis; then the motion of servomotor in z-axis denotes for drawing the profile of object touched by laser. Maintaining z-axis in fixed distance and the constant speed in y-axis, both of them have highly couple; hence, the adjustable parameters of a commercial servo-controller should be set at a restricted number, tunes in 10^{-7} of the differences.

For performing the optimization, the fitness function or model should be known clearly. Knowing the model of

TABLE 1. Adjustable-parameters of servo controller parameter boundary.

Parameter	K_A	K_B	K_C
Minimal	0.2	0.0	0.0
Maximal	11.0	1.0	1.0

servo-motor system is the crucial subject for controlling servo-motor; however, this information was hiding by the manufacturer due to trademark/copyright that include in its driver. The independency adjustment gave to user only for setting the adjustable-parameters values of a servo controller. So then, to set the certainly value of adjustable parameters, a complicated procedures are required for determining nonlinear and high couple correlation in the servomotor within mechatronic (mechanic-electronic) system as follow:

1. Considering any physical phenomena that occurred in running system such as jerk, collision, friction, positioning, viscosity of lubrication, and so on;
2. Differentiating procedure 1 to model of system;
3. Analysis the model using software for modelling of model;
4. Confirming the result of analysed model by equipment using frequency analyser; if the result is not satisfied, then loop from step 1.

Obviously, the analysis steps above takes many time and the huge budget as well. Therefore, some company prefer for using trial and error method by expert person (TEEP) for shift their loss, but this procedure requires many setting instances and disturbs the production process. Numerous experiments must be conducted to obtain a smaller error of response; hence, an advanced method is necessary to determine the feasible combination values.

Accordingly that situation above, for getting the appropriate setting of a servo controller with adjustable parameters in LAFS, this study aims for reducing the company's loss due by forming the model of model (metamodel) via NN. In this NN, we need only 40 experiments using LAFS equipment that determined by UD for building the metamodel; and then use the metamodel as fitness function used in HUDGA for getting the optimal setting of the adjustable parameters, finally confirmed with LAFS equipment.

In this case study, the LAFS has been in research to develop its performance. The genuine dimension of profile of object is determined to investigate the error of detecting profile via LAFS. Furthermore, after the error response is satisfied (less than 0.1mm), LAFS will be used for leading the gluing material process that affected by its profile. The ranges of adjustable parameters are listed in Table 1 for controlling z-axis distance between laser sensors and object, while the LAFS moves in y-axis to scan along object reference with 200 mm/s constantly movement then evaluated the trace point object every 0.005 seconds.

III. UniNeuro-HUDGA

In the proposed method, UD is embedded on an NN by using a genetic algorithm. First, UD is used for collecting 40 samples data input due to adjustable parameters settings, and the output response of LAFS is then verified. The data are used for forming the adjustable-parameters-based model of the metamodel [15], UniNeuro. Second, UD is used to set the combination of chromosomes in the optimization process by using the GA combined with UD, the HUDGA. The optimization procedure is explained as follows:

TABLE 2. UD's table of three parameters.

Run	K_A	K_B	K_C
1	3	4	3
2	2	1	4
3	1	3	1
4	4	2	2

A. ARRANGE EXPERIMENTAL DATA USING UD

In the optimization procedure, UD is used for determining adjustable-parameters sample input settings for using an appropriate solution set of systems. This composition is then used for obtaining the output. Finally, the data are used as the prediction of combinatory of model that recommended by UniNeuro. Regarding the arranged design of the pre-experiment on LAFSs, a UD table was downloaded in [17], further referred to as UD-web, developed by Wang and Fang. Using UD-web, we could devise a suitable table in relation to particular experimental conditions. The UD table is the design of experiment (DOE), which efficiently reduces the number of experiments; however, the obtained result closely matches the full factorial table. Generally, 3,125 experiments are necessary for applying 5 parameters with five levels for the full factorial, but using UD requires only six experiments for adequately presenting all feasible solutions. This is because UD spreads the possibility of solutions uniformly in the full search area; hence, the higher the number of UD experiments is, the more accurate the optimal solution [17], [20]–[24].

The experiment for UniNeuro is prepared as follows:

1. Determine the number of parameters. The minimal number of experiments is a number of parameters + 1, whereas the total level is equal to the number of experiments.
2. Choose the appropriate table from the UD-web and employ it in the experiment.

For instance, Table 2 shows the UD table from the UD-web for three parameters and four experiments. The run column presents the sequence of experiments. The number for columns K_A, K_B, and K_C are the ranking of the number of parameter values, which are placed in a particular sequence according to the UD table. This ranking covers all search areas uniformly from the lower bound to the upper bound; '1' is the lower bound, and '4' is the upper bound for each parameter. If it is necessary, the level of each parameter can be set as the dividing factor of the number experiments; for instance, Table 2 can be set into two levels individually by replacing sets 1 and 2 with 1, and then replacing 3 and 4 with 2.

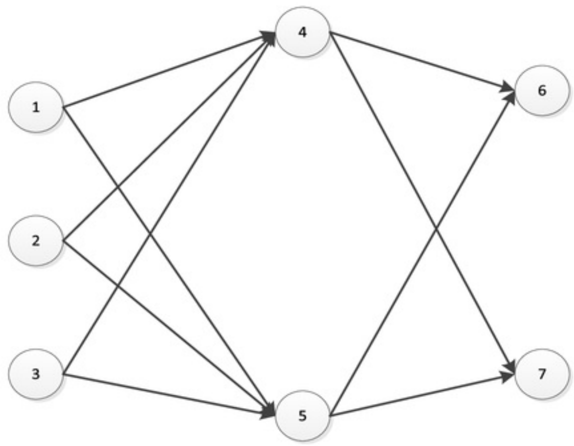

FIGURE 5. UniNeuro's schema.

B. FORMING A METAMODEL USING UniNeuro

An NN is applied in prediction methods by using the data input and then the output through the neural mechanism, for developing models of a model (metamodel) [18]. In this study, an NN was used to set up a metamodel by using the sigmoid activation formula. UD was used to collect the data for building a metamodel of an NN; thus, the approach is named UniNeuro.

Before being assigned to an NN, the data result from the experiment must be normalized using (1):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x_{norm} is the value that has been normalized on this parameter, x, the value of data in each experimental run; and x_{max} and x_{min} are the maximum and minimum values in this parameter, respectively. Normalization generates data values from 0 to 1. Using this method, the whole parameter is connected fairly evenly if it has unit differences; therefore, this method was used to develop a metamodel in NN, as shown in Fig. 5.

Fig. 5 shows that points 1, 2, and 3 are three input parameters (K_A, K_B, and K_C respectively); points 4 and 5 are two neurons in a single hidden layer; finally, points 6 and 7 are the objectives, the maximal error and total error, calculated using (2) and (3), respectively:

$$maximal_{error} = max\left(\left|D_{reference} - D_{response}\right|\right) \tag{2}$$

$$total_{error} = \sum_{i=1}^{n} \left|D_{reference} - D_{response}\right| \tag{3}$$

where $maximal_{error}$ = each analysed point evaluation for determining the largest error, $D_{reference}$ = the reference profile's dimension, $D_{response}$ = the response result obtained using the LAFS, $total_{error}$ = the total error for a whole point, and n = the number of evaluated points from the adjustable-parameters setting.

UniNeuro is employed in the optimization procedure as follows:

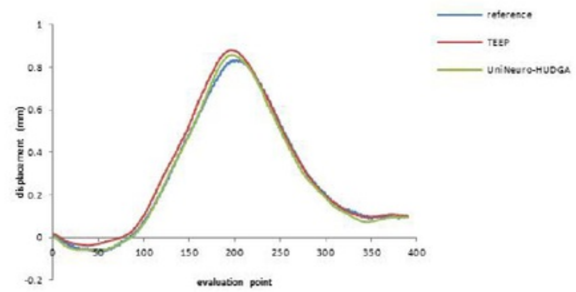

FIGURE 6. The tracking objects result setting #1.

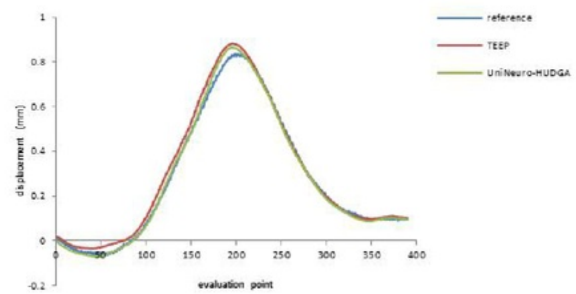

FIGURE 7. The tracking objects result setting #2.

Step 1: Determine the NN design, the numbers of neurons and hidden layers, the objective, learning rate (α), initial weight in each point neuron, and error criteria by using the mean square error (MSE) for objectives 1 and 2. MSE is used to avoid the overfitting of the model [15].

Step 2: Arrange the normalized training data that are collected in the UD setting in the input and output of the NN, similarly to the testing data but with fewer experiments.

Step 3: Calculate the weight factor (using the sigmoid activation formula in this case).

Step 4: Build a metamodel for the two objectives. The metamodel consists of several specific weights implemented according to the parameters for constructing values close to a real solution.

Step 5: Review the MSE for the two fitness values of each objective of the metamodel by using the testing data, a process that is completely different from setting with training data. If the result is more than the criteria (MSE), return to step 3; otherwise, continue to step 6.

Step 6: When the metamodel is formed, it is used as the fitness function in the HUDGA with a single objective that is the sum of two objectives for a smaller-the-better target.

The LAFS evaluates numerous response corrections, and then chooses the maximal error and total error as UniNeuro's objectives, which are affected by the adjustable-parameters input setting.

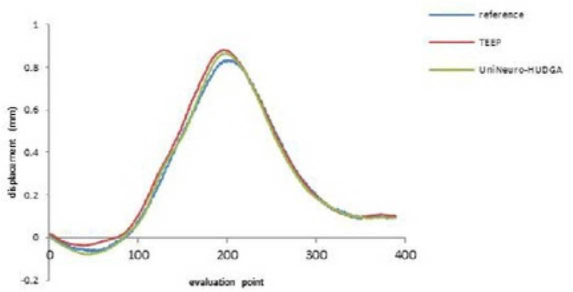

FIGURE 8. The tracking objects result setting #3.

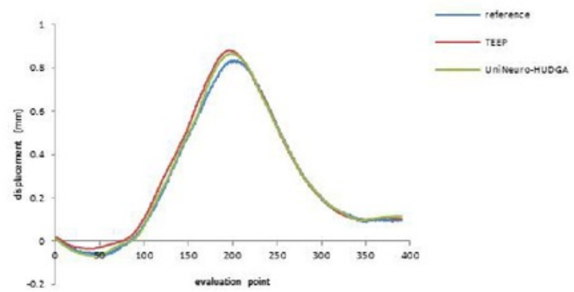

FIGURE 9. The tracking objects result setting #4.

C. OPTIMIZING THE RESULT USING HUDGA

After the metamodel is formed using UniNeuro, the optimal parameter setting achieved using the HUDGA is used in the optimization procedure as follows:

Step 1: Determine the HUDGA parameters, population number (PN), selection number (SN), generation number (GN), and Euclidean number (EN).

Step 2: Initialization is performed to generate a parent chromosome. For 40 chromosomes obtained from the UniNeuro real training data and testing data, this procedure aims to reduce the error caused by the prediction model (metamodel). Of the remaining PNs involve using a random number [0-1] for three parameters (genes). Each chromosome is then evaluated in determining the sum of the maximal error and total error as a fitness value. Finally, the fitness value is ranked for smaller-the-better.

Step 3: The selection process involves a roulette wheel; all the parent chromosomes occupy the roulette wheel according to their probability of occurring in the whole result. The roulette wheel is then rotated for selecting a chromosome pair; obviously, the same chromosomes in a pair must be avoided to increase the diversity of the solution set [26].

Step 4: All chromosomes from step 3 are crossed in this crossover procedure by using the single-point crossover method in a pair of chromosomes.

Step 5: All chromosomes from step 3 are mutated in this mutation procedure conducted using one gene randomly. One gene is randomly chosen for each chromosome to generate a new gene by a random number [0-1].

Step 6: To improve the variation of children, the chromosomes from crossover and mutation are combined, and then two of them are selected randomly. The selected chromosomes are generated in experiments by using UD for three parameters and eight combinations for two levels. Principally, this procedure is based on [26] by replaces Taguchi DOE for two levels using UD two levels.

Step 7: The parent and child's chromosomes are combined into a parent chromosome for the next iteration by selecting a PN. The chromosome with the lowest fitness value is stored as the best chromosome and is updated every generation, while the remaining chromosomes are selected in step 7.

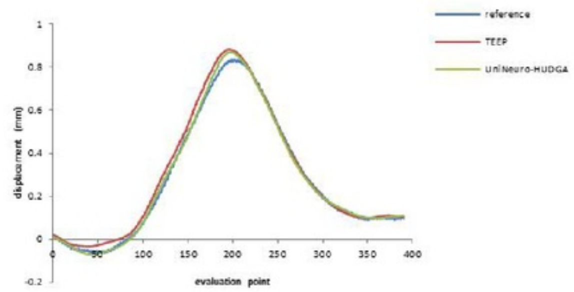

FIGURE 10. The tracking objects result setting #5.

Step 8: For maintaining the diversity of the solution for each generation, the remaining chromosomes in step 7 are sorted and then filtered using the Euclidean distance method and selected for an NP-1 number of chromosomes. The Euclidean distance is used as the vector distance between a pair of chromosomes. A higher value of the Euclidean distance produces fewer alternative solutions [27].

Step 9: This study used a number iteration as a stopping criterion. If the number of performed iterations is lower than the GN, then the process is repeated to step 3. If the iteration number is fulfilled, then continue to step 10.

Step 10: The optimal result is displayed and verified according to adjustable-parameters in LAFS equipment to approve its reliability. The optimal setting result changes to the real number of settings through the opposite normalization procedure. Finally, the optimal setting is confirmed using the real equipment for verifying the maximal error as the objective of this research.

IV. RESULTS AND DISCUSSION

For examining the optimal setting of adjustable-parameters-based controllers in LAFSs, the UniNeuro-HUDGA was programmed in Matlab software and run on a modern CPU

TABLE 3. Result of confirmations measurement.

Method	K_A	K_B	K_C	maximal error	total error	average error
TEEP	10.5000000	0.0039000	0.0000000	0.0827	9.0699	0.023256
UniNeuro-HUDGA	10.9993821	0.3399421	0.6499968	0.05168 (mean) *0.0047(standard deviation)*	4.96506 (mean) *0.534 (standard deviation)*	0.012731 (mean) *0.00137 (standard deviation)*
UniNeuro-HUDGA	10.9997263	0.3398979	0.6499668			
UniNeuro-HUDGA	10.9997166	0.3399721	0.6499134			
UniNeuro-HUDGA	10.9994249	0.3399803	0.6499898			
UniNeuro-HUDGA	10.9997513	0.3399916	0.6499091			
UniNeuro-HUDGA	10.9995627	0.3399892	0.6499820			
UniNeuro-HUDGA	10.9996221	0.3399765	0.6499893			
UniNeuro-HUDGA	10.9998759	0.3399553	0.6499622			
UniNeuro-HUDGA	10.9988937	0.3399505	0.6499996			
UniNeuro-HUDGA	10.9971829	0.3399904	0.6499226			

Where : Max is maximal error of detecting by LAFS; Total Error is sum absolute error; Standard deviation result from 10 running confirmation of UniNeuro-HUDGA is served by bold number.

(Intel®Core ™i7-2630 QM, 2.0 GHz). Thirty experiments for training data and 10 experiments for testing data were performed using the UD setting, which was applied for building the metamodel within UniNeuro. The metamodel was then used as the fitness function in the HUDGA for obtaining the optimal adjustable-parameters setting with the minimal of maximal error and total error calculated using (2) and (3), respectively.

UniNeuro involves using the following parameters: the learning rate $\alpha = 0.1$, MSE error standard $= 0.01$, the initial weight for $w_{n=1-3}$, $_{m=4,5}$ decided by randomly from -0.5 to 0.5, whereas the initial weight for $w_{n=4-5,m=6,7}$ determined via randomly from -1 to 1, and then $\theta_{n=4-7}$ selected randomly from -0.5 to 0.5. In addition, the HUDGA parameters are set as follows: PN = 1,000; SN = 0.8 × PN; GN = 10,000; and EN = 0.2. Moreover, for confirming the robustness of obtaining the metamodel, UniNeuro is run 10 times.

In this study, 40 experiments were conducted, consisting of 30 training data and 10 testing data applied on the UD table individually. The two classes of data were utilised to build the model of the model within UniNeuro. The metamodel was then used as the fitness function in the HUDGA.

Table 3 shows the comparing result of using TEEP and UniNeuro-HUDGA. In the first row, data of TEEP only recommend one peak performance after trial and error more than 2 work days; however, UniNeuro-HUDGA has 10 feasible parameters value that suggested in its running that totally consumes 450 minutes from preparing data, then 10 running UniNeuro-HUDGA program and finally confirmation. The result of UniNeuro-HUDGA is presented in average and its standard deviation. Compared with the result from TEEP, all optimized settings generated by the UniNeuro-HUDGA can perform at outstanding performance not only in the maximal error but also in total error, average error, and standard deviation of the data; therefore, this result supports that all settings used in the UniNeuro-HUDGA are outperformed. Moreover, the single optimal setting that outperforms all the criteria must be improved because the stability of UniNeuro is affected by stochastic response.

Table 3 also shows the parameter setting of TEEP and UniNeuro-HUDGA, thus the response of LAFS shown in Fig. 6 to 15. Fig. 6 to 15 show the reference profile of the object in includes the two LAFSs responses from TEEP and one of sample of UniNeuro-HUDGA. The first shoot of point correction is used for referencing zero point, then along the moving of sensor draws the profile of object; thus in Fig. 6 to 15 shows (-) area when the profile is lower than first shoot, and vice versa.

The results proved that UniNeuro can modify the model of model-metamodel used as the fitness function in the HUDGA. In other words, using UD for determining the experimental training data and testing data in UniNeuro is highly efficient for capturing or predicting the real model of the servo controller with adjustable-parameters. Certainly, only 40 experiments can produce 10 optimal settings, because some modifications are necessary for enhancing the robustness of UniNeuro to improve its probability such as adaptive fuzzy modelling, which uses such valuable information for improving the auto error correction model [27]–[32].

The optimization procedure was finalised using the metamodel from UniNeuro for the fitness function in the HUDGA. In the optimization procedure, the HUDGA demonstrated its performance by generating the true result for optimal setting adjustable-parameters; thus, this step can obtain several true optimization settings and can avoid being trapped in local optima.

Overall, the results indicated that the proposed algorithm can effectively solve this problem, because it requires only 10 runs by using the 40 real data collected from UD, with 100% success. It is obvious that the proposed algorithm outperformed the TEEP method, simplified the setting

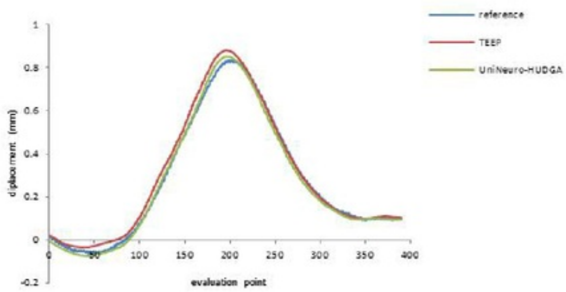

FIGURE 11. The tracking objects result setting #6.

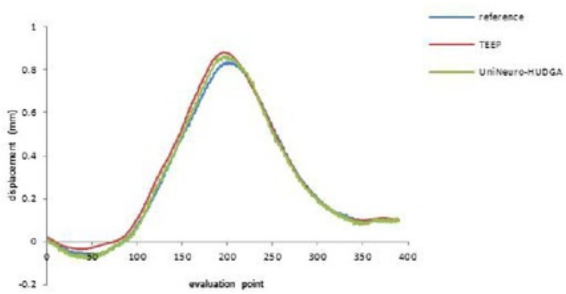

FIGURE 12. The tracking objects result setting #7.

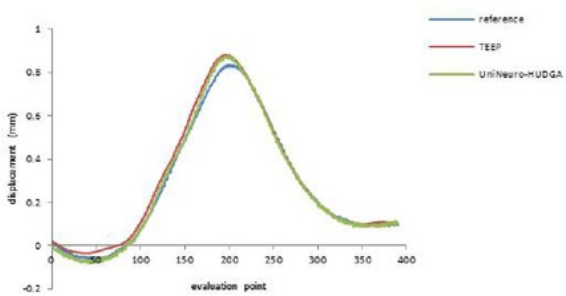

FIGURE 13. The tracking objects result setting #8.

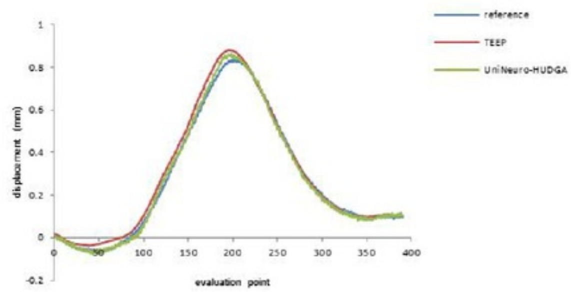

FIGURE 14. The tracking objects result setting #9.

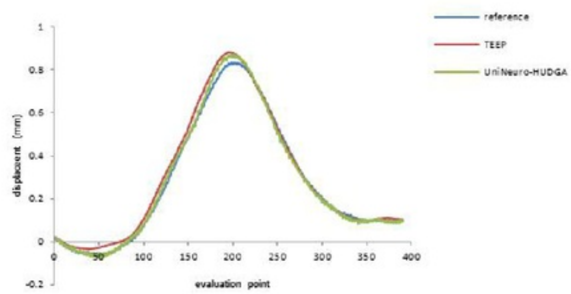

FIGURE 15. The tracking objects result setting #10.

process, and saved experimental time. However, the reliability of the proposed algorithm must be improved for optimizing the procedure. Furthermore, for particular aims, the speed of LAFS scanning or the robustness of the setting can be a supplementary objective.

Additionally, using UD in assigning the experiment for training data was proven; in this case, the information about the model could be suggested even the trend of graphic result neither. Instead, UD can promote a small sample that represents a whole feasible setting of adjustable-parameters; this is the intention of UD, to assign the CD a number representing the quality of uniformity (a lower CD indicates higher uniformity). Moreover, UD can be easily used for resolving problems that require capturing the whole system with limited data because of constraints such as time, a workforce shortage, and budget. Therefore, UD can be developed by the user, particularly if the number of parameters is not available on the UD-web (maximum of 29 parameters). By employing CD as a criterion of the table and then using it in an optimization design for the cost function or a smaller-the-better target; obviously, this issue will draw considerable attention because of DOE effectiveness in corresponding optimization problems.

Comparing the Taguchi design with the uniform design, UD is more efficient in a higher number of parameters, where the Taguchi design should be record the level to determine the experiment, UD does not. UD can be easily implemented by the user, but the Taguchi design cannot. The aim of the Taguchi design is to propose a robustness setting from the appropriate combination that is shown by the signal-to-noise ratio then analysed by the mean effect of each parameter [33].

V. CONCLUSION

This study sought to determine the optimal setting for the servo controller with adjustable-parameters setting inputs of LAFSs, for obtaining least-error response. However, because the model controlling system function is unknown, the optimization of the parameters was developed using a metamodel of the NN, formed using the training and testing data retrieved by UD, named UniNeuro. Furthermore, the HUDGA, which is embedded in UD, was used to optimize the adjustable-parameters settings according to the metamodel as the fitness function. The HUDGA was initialized by combining real data from UniNeuro and added through random generation Roulette wheel selection and was then applied to convey chromosomes to crossover and individual mutation. UD was performed for enriching the chromosomes from crossover and mutation. Finally, the Euclidean distance was used for maintaining the diversity of the solutions.

The results of this study generated 10 optimized adjustable-parameters settings that outperformed TEEP in obtaining a least-error response. Compared with the TEEP method, this method proved to be significantly faster because it requires only 40 data as the training data and testing data for UniNeuro to develop a metamodel. Using UD is highly efficient for application in DOE for generating the training data and testing data for UniNeuro. This is because this method can spread uniformly in a solution search space for obtaining results close to full factorial while markedly reducing the number of experiments. Furthermore, the accuracy of the model needs improvement though arrangement of the structures of metamodelling, such as using an adaptive approach [27]–[32] and objective criteria to create multi constraints and robust configurations.

The findings of this research are useful for optimization, even when the model information is undetermined. This advanced prediction approach and metamodeling mitigate the input and response for forming the linear approach function; obviously, this model is not true because the true model may be nonlinear, even when linear regression is used. Therefore, the proposed method is worth being applied to solving real problems in which the information system model is unknown. Even if the optimal solution is close to the only the optimal solution, the number of experiments is reduced when compared with the TEEP method. For instance, in this study, three inputs of adjustable-parameters, which were undetermined, succeeded in optimization through least error response, and required only 40 experiments for generating an advance setting. Obviously, if the TEEP method or full factorial is used, the number of experiments would be increased dramatically because of the narrow range in the level of each parameter.

REFERENCES

[1] J. M. Di Martino, A. Fernández, and J. A. Ferrari, "One-shot 3D gradient field scanning," *Opt. Lasers Eng.*, vol. 72, pp. 26–38, Sep. 2015.

[2] S. Kim, H. Kim, W. Yoo, and K. Huh, "Sensor fusion algorithm design in detecting vehicles using laser scanner and stereo vision," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 4, pp. 1072–1084, Apr. 2016.

[3] Y. Wang and H.-Y. Feng, "Effects of scanning orientation on outlier formation in 3D laser scanning of reflective surfaces," *Opt. Lasers Eng.*, vol. 81, pp. 35–45, Jun. 2016.

[4] Y. Liu, T. Bobek, and F. Klocke, "Laser path calculation method on triangulated mesh for repair process on turbine parts," *Comput.-Aided Design*, vol. 66, pp. 73–81, Sep. 2015.

[5] C. Zhou, H. Deng, and G. Chen, "Study on methods of enhancing the quality, efficiency, and accuracy of pulsed laser profiling," *Precis. Eng.*, vol. 45, pp. 143–152, Jul. 2016.

[6] J. A. Polyblank, J. M. Allwood, and S. R. Duncan, "Closed-loop control of product properties in metal forming: A review and prospectus," *J. Mater. Process. Technol.*, vol. 214, pp. 2333–2348, Nov. 2014.

[7] S. T. Holmstrom, U. Baran, and H. Urey, "MEMS laser scanners: A review," *J. Microelectromech. Syst.*, vol. 23, no. 2, pp. 259–275, Apr. 2014.

[8] S. Goel and B. Lohani, "A motion correction technique for laser scanning of moving objects," *IEEE Geosci. Remote Sens. Lett.*, vol. 11, no. 2, pp. 225–228, Jan. 2014.

[9] X. Zhang, W. Zhu, X. Feng, and F. Pfaender, "Research on the reconstruction of city building with three dimension laser scanner," in *Proc. IET Int. Conf. Smart Sustain. City (ICSSC)*, Aug. 2013, pp. 32–35. [Online]. Available: http://ieeexplore.ieee.org/document/6737794/

[10] B. Xue, X. Yang, and J. Zhu, "Architectural stability analysis of the rotary-laser scanning technique," *Opt. Lasers Eng.*, vol. 78, pp. 26–34, Mar. 2016.

[11] B. Sun and B. Li, "A rapid method to achieve aero-engine blade form detection," *Sensors*, vol. 15, pp. 12782–12801, Jun. 2015.

[12] A. Pan, J. Si, T. Chen, C. Li, and X. Hou, "Fabrication of two-dimensional periodic structures on silicon after scanning irradiation with femtosecond laser multi-beams," *Appl. Surf. Sci.*, vol. 368, pp. 443–448, Apr. 2016.

[13] F. Santoso, M. A. Garratt, M. R. Pickering, and M. Asikuzzaman, "3D mapping for visualization of rigid structures: A review and comparative study," *IEEE Sensor J.*, vol. 1, no. 6, pp. 1484–1507, Mar. 2016.

[14] Y. Zhuang, F. Yan, and H. Hu, "Automatic extrinsic self-calibration for fusing data from monocular vision and 3-D laser scanner," *IEEE Trans. Instrum. Meas.*, vol. 63, no. 7, pp. 1874–1876, Jul. 2014.

[15] Y. Zhang, G. Tao, and M. Chen, "Adaptive neural network based control of noncanonical nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 27, no. 9, pp. 1864–1877, Sep. 2015.

[16] L. Yong-Qiu and L. Xiao-Feng, "Design of Car coating system based on PLC," in *Proc. IEEE Workshop Adv. Res. Technol. Ind. Appl. (WARTIA)*, Sep. 2014, pp. 987–989.

[17] K.-T. Fang and Y. Wang. (2004). *Uniform Design*. [Online]. Available: http://www.math.hkbu.edu.hk/UniformDesign/

[18] G. Dreyfus, *Neural Networks: Methodology and Applications*. Springer, 2005, pp. 1–80.

[19] K.-T. Fang and D. K. Lin, "Uniform experimental designs and their applications in industry," in *Handbook of statistics*, vol. 22. Apr. 2003, ch. 4, pp. 131–170. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0169716103220061X

[20] S. F. Yang and W.-T. K. Chien, "Electromigration lifetime optimization by uniform designs and a new lifetime index," *IEEE Trans. Rel.*, vol. 64, no. 4, pp. 1158–1163, Dec. 2015.

[21] K.-T. Fang, R. Li, and A. Sudjianto, *Design and Modeling for Computer Experiments*. Boca Raton, FL, USA: CRC Press, 2005, pp. 67–103.

[22] Y.-R. Cai and J.-H. Chou, "Uniform design method to finding the optimal parameters for machine roughing," in *Proc. Int. Conf. Syst. Sci. Eng. (ICSSE)*, Aug. 2016, pp. 1–3. [Online]. Available: http:// ieeexplore.ieee.org/ abstract/ document/7551639/

[23] P.-K. Huang and J.-H. Chou, "Uniform design method to finding the optimal parameters for support vector machine," in *Proc. Int. Conf. Syst. Sci. Eng. (ICSSE)*, Aug. 2016, pp. 1–3. [Online]. Available: http:// ieeexplore.ieee.org /abstract/ document/7551638/.

[24] T.-H. Lin and J.-H. Chou, "Study on the optimal parameters of artificial neural networks by applying uniform design," in *Proc. Int. Conf. Syst. Sci. Eng. (ICSSE)*, Aug. 2016, pp. 1–2. [Online]. Available: http://ieeexplore.ieee.org/ abstract/ document/7551640/

[25] S.-Q. Lu and J.-H. Chou, "Optimal strategy parameters for particle swarm optimizer via the uniform design," in *Proc. Int. Conf. Syst. Sci. Eng. (ICSSE)*, Aug. 2016, pp. 1–2. [Online]. Available: http://ieeexplore.ieee.org/ abstract/ document/ 7551637/

[26] D. H. Al-Janan and T.-K. Liu, "Path optimization of CNC PCB drilling using hybrid Taguchi genetic algorithm," *Kybernetes*, vol. 45, no. 1, pp. 107–125, Jan. 2016.

[27] M. Greenacre and R. Primicerio, *Measures of Distance Between Samples: Euclidean*. Fundacion BBVA Publication, Dec. 2013, pp. 978–984.

[28] P. Palmes and S. Usui, "Robustness, evolvability, and optimality of evolutionary neural networks," *Biosystems*, vol. 82, pp. 168–188, Nov. 2005.

[29] M. Chen, S. S. Ge, and B. V. E. How, "Robust adaptive neural network control for a class of uncertain MIMO nonlinear systems with input nonlinearities," *IEEE Trans. Neural Netw.*, vol. 21, no. 5, pp. 796–812, May 2010.

[30] Z. Chu, D. Zhu, and S. X. Yang, "Observer-based adaptive neural network trajectory tracking control for remotely operated vehicle," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. PP, no. 99, pp. 1–13, Apr. 2016, doi: 10.1109/TNNLS.2016.2544786.

[31] C. Sun, W. He, W. Ge, and C. Chang, "Adaptive neural network control of biped robots," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. PP, no. 99, pp. 1–12, May 2016, doi: 10.1109/TSMC.2016.2557223.

[32] F. Zhao, S. S. Ge, F. Tu, Y. Qin, and M. Dong, "Adaptive neural network control for active suspension system with actuator saturation," *IET Control Theory Appl.*, vol. 10, no. 14, pp. 1696–1705, Sep. 2016.

[33] W. Y. Fowlkes and C. M. Creveling, *Engineering Methods for Robust Product Design*. Reading, MA, USA: Addison-Wesley, 1995, pp. 63–91.

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