IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received October 18, 2020, accepted October 28, 2020, date of publication November 4, 2020, date of current version November 18, 2020.

*Digital Object Identifier 10.1109/ACCESS.2020.3035788*

# Repetitive Control Process for Periodic Disturbance Cancellation Using Data Classification With a Fuzzy Regression Approach

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This work was supported by the Academia Sinica, Taiwan, under Grant 108-2-1-11-23.

**ABSTRACT** The utilization of a repetitive controller to cancel periodic disturbance or noise in mechanical systems has become increasingly important for industrial applications. In this study, a repetitive control process was developed using a data classification method, with a fuzzy regression approach and basis function, to reduce tracking errors in feedback controllers. First, a system model using the basis function is illustrated to compute the matched basis functions and their associated coefficients. A real case example of improving the focus of an electron beam subjected to periodic fluctuations has been described for verification and error analysis. Next, model algorithms containing pure and fuzzy regression are introduced into a repetitive feedback control system to reduce tracking errors caused by a periodic disturbance. System output data are categorized using fuzzy inference rules as similar data forming a single group are typically more reliable than the entire output data. The fuzzy theorem approach adopts a Gaussian membership function for system output variables owing to uncertainties that arise from modeling errors, environmental noise, etc. It is determined that the repetitive control process based on data classification with a fuzzy regression approach is more effective than using a pure regression approach. Increasing the number of data classifications initially improves accuracy; however, this decreases when the number of data classifications continues to increase. The optimal root-mean-square output tracking error convergence value was determined as $10^{-14.09}$ when the system output data was classified into four categories, demonstrating the satisfactory reduction of a periodic disturbance. Similar results were obtained using the pure regression algorithm, where the lowest averaged verification error was 2.71% for the linear basis function model, with data classified into four categories, and this corresponded to an average prediction error of 3.86%.

**INDEX TERMS** Data classification, disturbance cancellation, fuzzy regression, repetitive control.

## I. INTRODUCTION

A control scheme comprises two control methods: a linear feedback mechanism and a feedforward learning strategy. Control systems are generally based on the principle of feedback, wherein the signal to be controlled is compared against the required reference signal, and the difference is used to compute the corrective control measures [1]. A feedback control system often results in errors due to the effect of repeated perturbations, leading researchers to attempt to suppress the imbalanced signal or vibration. During each iteration, linear feedback provides system stability while maintaining its state error within a uniform range. Optimal solutions to such problems generally entail repetitive and learning control.

Accordingly, reference [2] proposed an optimal control system with velocity-acceleration feedback in which numerical simulations revealed that the proposed control scheme was almost as effective as an optimal control system with state feedback. Expectedly, a feedback-based method, that is, repetitive control, was designed to track periodic reference trajectories or eliminate periodic interference [3]. Reference [4] proposed a combined control strategy that integrated

The associate editor coordinating the review of this manuscript and approving it for publication was Choon Ki Ahn.

offline iterative learning control and improved internal model control to enhance the waveform replication performance of an electro-hydraulic shaker. However, their control strategy posed challenges in real-time implementations, including limited sampling time to evaluate candidate solutions. Therefore, reference [5] presented a real-time implementation of the iterative process for a direct particle swarm controller. Reference [6] proposed a co-design algorithm to obtain the control gain and event trigger parameters.

Repetitive control has proven to be an effective method in eliminating the effects of periodic disturbances on a control system [7]. For example, reference [7] proposed a novel second-order repetitive control that achieved second-order behavior but used data from only one period in the past. In addition, a repetitive control approach was considered for an inverter operation owing to its better controllability and accuracy under periodic disturbance conditions [8]. Reference [9] proposed a fast repetitive control (FRC) scheme with harmonic correction loops for a three-phase three-wire shunt active power filter applied in a weak power grid, introducing a cumulative error cancellation loop into the FRC to improve the harmonic detection accuracy when the grid frequency drifted. Reference [10] proposed a fractional-order repetitive controller to reject periodic disturbances acting on a time-invariant-linear-stable-, possibly non-minimum phase-plant while discussing the conditions of the system's absolute stability in the presence of saturation nonlinearities. Reference [11] addressed a master-slave synchronization control problem for current-fed DC and permanent magnet synchronous motors, with entirely uncertain parameters, and proposed an innovative disturbance cancellation technique, proving that an output-feedback-adaptive-nonlinear control scheme generalizes the classical internal-model-based input law. Reference [12] proposed that typical repetitive control methods initially address all frequencies of a given period, while the matched basis function repetitive control individually addresses each frequency, finding error components at these frequencies using only frequency response knowledge at the addressed frequencies. Reference [13] summarized developments in linear repetitive control, which represented an effective overall design approach, allowing the user to optimize performance; this involved the design of a compensator, zero-phase low-pass filter, and interpolator.

The fuzzy set theory proposed by [14] has been widely used in management, decision-making, control, evaluation, and academic research. The focus of fuzzy modeling for control involves selecting an appropriate model structure, obtaining the dynamic fuzzy model (that is, fuzzy recognition) from the process measurement, and designing a nonlinear controller based on the fuzzy model [15]. To demonstrate the varied applications of fuzzy theory, reference [16] used a fuzzy input estimation method for active vibration control in beam-rotating machinery systems. Reference [17] proposed an innovative fuzzy regression method to assess the potential vulnerability of bridges subjected to earthquakes. Reference [18] applied fuzzy controller design to a wind turbine for load reduction. Reference [19] proposed a fuzzy logic control scheme that used a magnetorheological damper to withstand near-earthquake ground motion to decrease construction vibration and optimize the membership function and fuzzy rules of the fuzzy controller through genetic algorithms. Reference [20] developed a temperature control system using fuzzy logic and ensured the required output response via a feedback controller. Reference [21] applied an actively tuned mass damper to control the seismic response of an 11-story building, in which a fuzzy logic controller was used to deal with uncertainty and nonlinearity, and particle swarm optimization was applied to the structure to optimize the fuzzy logic controller's parameters. Reference [22] applied a fuzzy logic technique for optimizing general control structures as well as secondary voltage and frequency controllers that exhibited high performance and ideal response under different load changes. Reference [23] proposed the use of proportional-integral-type sliding mode manifolds to mitigate the effects of static tracking errors. To suppress the inherent chatter, a fuzzy logic system was used to estimate the uncertain dynamics due to its universal approximation ability; the coordinated control target of the robot attitude and uncertainty suppression were simultaneously achieved.

Stability analysis and system design have also been the most important issues concerning fuzzy control of structures and systems. A fuzzy control scheme has been successfully applied to the control design of structures and systems. Reference [24] developed a fuzzy method, based on the linear matrix inequality (LMI), which modeled and controlled the vibration of geometrically nonlinear flexible plates; the fuzzy dynamic output feedback control law used a parallel-distributed compensation technology to design a model in which stability analysis and interference filtering problems were studied using the LMI method. In addition, as data categorization intrinsically leads to improved reliability, reference [25] proposed a questionnaire classification method based on factor analysis to improve the assessment's reliability of the working conditions, without affecting the integrity of the questionnaires for construction companies in both Taiwan and China. Reference [26] established a Taiwan-based road construction bidding price prediction model that illustrated a data classification system using fuzzy set theory to ensure accurate predictions.

Based on the aforementioned arguments and the previous work by [27], [28] on disturbance rejection, as well as to highlight the importance of each design framework based on the problem statement and why the proposed method is necessary to be designed for this particular system, this study developed a repetitive control process using a fuzzy regression approach, with basis function feedback to decrease tracking errors or disturbances. First, a system model using the basis function was used to compute the matched basis functions and their associated coefficients. For verification and error analyses, a case example for improving the electron beam focus was used. Second, model algorithms containing pure and fuzzy regression were compared by introducing them into a repetitive feedback control system to reduce tracking errors caused by a periodic disturbance. Third, the repetitive control mechanism via data classification with a fuzzy regression approach proved to be more effective than that with the pure regression approach. The conclusions drawn indicated that an increase in the data classification number improved the accuracy; however, the accuracy decreased when the data classification number continued to increase. Similar results were obtained using the pure regression algorithm, where the lowest averaged verification error was 2.71% for the linear basis function model, with data classified into four categories, and this corresponded to an average prediction error of 3.86%.

## II. SYSTEM MODEL WITH A LINEAR REPETITIVE CONTROL PROCESS

The linear basis functions are described in general, as follows:

$$\mathrm{y}(\mathrm{X}, \mathrm{W}) = \sum_{\mathrm{j}=0}^{\mathrm{M}-1} \omega_{\mathrm{j}} \varnothing_{\mathrm{j}}(\mathrm{X}) = \mathrm{W}^{\mathrm{T}} \varnothing(\mathrm{X}), \tag{1}$$

where $\varnothing_{\mathrm{j}}(\mathrm{X})$ denotes the basis functions. Typically, $\varnothing_0(\mathrm{X}) = 1$ and thus, $\omega_0$ denotes bias.

Repetitive control laws are represented by the following [27], [28]:

$$y = T_y\alpha = T_y\beta \text{ (Let } \alpha = \mathrm{I}\beta), \tag{2}$$

$$\alpha\,(i) = \alpha(i-1) + y_{i-1}[y\,(i-1) - T_y(i-1)\alpha(i-1)], \tag{3}$$

$$\beta\,(i) = \beta\,(i-1) + \Gamma\left(\delta^* - \alpha\,(i)\right), \tag{4}$$

here, Eq. (2) represents the steady-state response, where $u = T_u\beta$, $T_u$ denotes the selected discrete-time basis function, $T_y$ denotes the corresponding output basis function, column matrices $\alpha$ and $\beta$ correspond to the coefficients of the output and input basis functions, respectively, and I is the identity matrix. Equation (3) represents the estimate of $\alpha\,(i)$ at each time-step, where $y_i$ is not a data function but can be determined *a priori* and $T_y(i)$ is determined from $T_y$. Equation (4) represents a linear repetitive control law for real-time implementation, where $\Gamma$ corresponds to a square matrix of learning gains, and $\delta^*$ denotes the required trajectory in terms of components of the output basis functions.

The repetitive control laws are demonstrated using a real case example, wherein the focus of an electron beam subjected to periodic fluctuations is improved [28] via the following transfer function:

$$T\,(s) = \frac{8.8\omega^2}{(s+8.8)(s^2+2(0.5)\omega s+\omega^2)} \tag{5}$$

in which $\omega = 37$ rad/s and the sampling rate is 64 Hz. The desired trajectory is zero, with a periodic disturbance, constituting a disturbance cancellation problem. Converting the transfer function to state-space form yields the controller canonical form, as follows:

$$x\,(i+1) = A_d x\,(i) + B_d u(i), \tag{6}$$

$$y(i) = C_c x\,(i+1) + D_c u(i). \tag{7}$$

so as to obtain the parameters $A_d$, $B_d$, $C_c$ and $D_c$ for the transfer function [28]. The operational flow chart for the system model with linear repetitive control laws is shown in Fig. 1, where Equation (7) is obtained from Equation (6) in an orderly fashion.

## III. MODEL ALGORITHMS

### A. PURE REGRESSION

For linear regression algorithms, [29] proposed a model specification in which the dependent variable $y_i$ is a linear combination of parameters. In regression modeling, with $i$ data points, there exists an independent variable $T_y(i)$ and the corresponding parameters $a$ and $b_i$, expressed as follows:

$$y_i = a + b_1 T_y\,(1) + b_2 T_y\,(2) + b_3 T_y\,(3) + \ldots + b_i T_y\,(i) + \varepsilon_{\mathrm{i}}. \tag{8}$$

Hence, using Eq. (8), a pure regression algorithm was introduced into a repetitive feedback control system to reduce tracking errors, as shown in Fig. 1.

### B. FUZZY REGRESSION

Owing to uncertainties that arise from modeling errors, environmental noise, and other measurement errors, the other model algorithm introduced the fuzzy theorem into the regression algorithm. The fuzzy concept is used to measure the magnitudes of phenomena [30], while fuzzy clustering is used to arrange similar data points into the same cluster [31]. In the study, both phenomena were grouped and classified such that different and discrete counting units were defined. It was feasible to assign all observations to mutually exclusive categories and, hence, they could be appropriately quantified. Fuzzy reasoning is a computation process that uses fuzzy logic methods to obtain new fuzzy propositions as conclusions under the condition of given fuzzy propositions [32]. Fuzzy reasoning can be divided into fuzzification, fuzzy logic reasoning, and defuzzification. Fuzzy variables form the bases for constructing fuzzy systems that utilize the complexity weights of used cases to analyze problems.

Conversely, fuzzy set theory permits gradual assessment of the membership of elements in a set; this is described with the aid of a membership function valued in the real unit interval [0, 1] [33]. Fuzzy membership functions primarily use triangular, trapezoidal, Gaussian, and generalized Bell membership functions, as shown in Fig. 2. The data used in this study is approximately distributed and thus a Gaussian membership function (Fig. 2 (c)) is used to represent the degree of ambiguity for the input and output variables. The mathematical description form of the Gaussian membership function is expressed as follows:

$$\mu(T_y(i)) = \mathrm{e}^{-\frac{(T_y(i)-\mathrm{c})^2}{\sigma^2}} \tag{9}$$

where $c$ denotes the center position of the Gaussian membership function, $\sigma$ denotes the width of the Gaussian membership function, and $T_y\,(i)$ denotes the input signal in the equation. This study utilized the center-of-gravity method

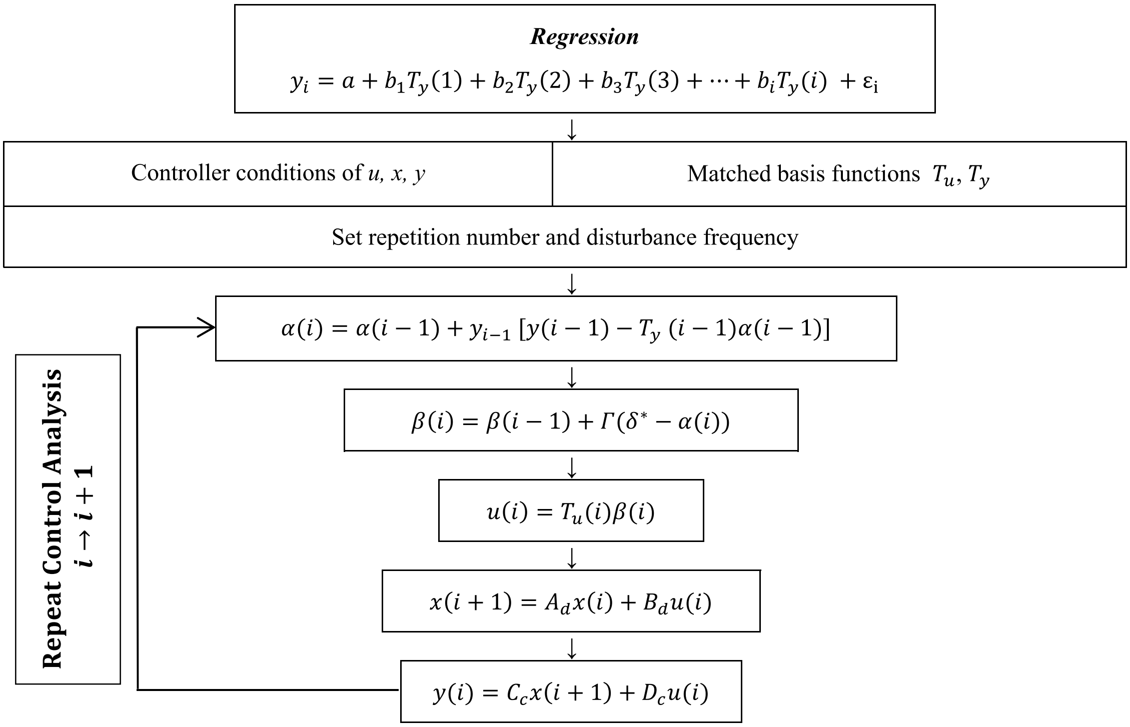


**FIGURE 1. Pure regression operational flow chart for the system model with linear repetitive control laws, which resembles input-output block diagram of the feedback closed loop control system with the proposed technique.**

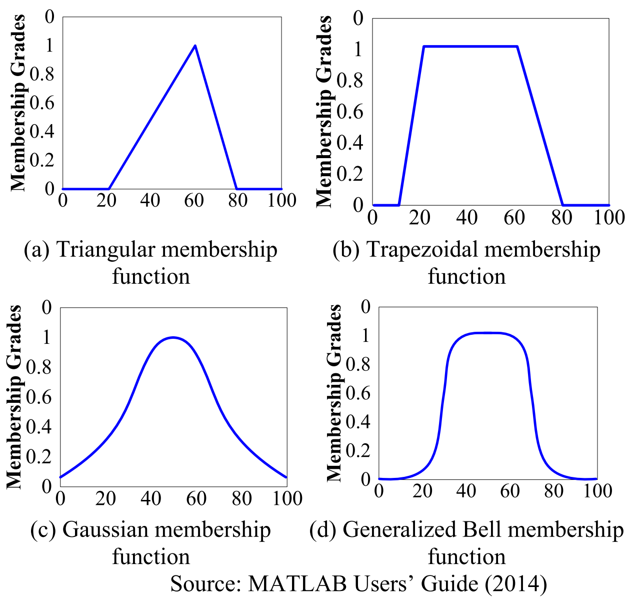


**FIGURE 2. Fuzzy logic membership functions.**

to solve fuzzification and compute the enclosed area of the width of the membership function and its membership function as a clear value to the center of the fuzzy numbers. The formula for system output variables, $y_{\text{output}}(i)$ is expressed as follows

$$y_{\text{output}}(i) = \frac{\int_{T_y(i)} T_y(i) \cdot \mu\left(T_y(i)\right) dT_y}{\int_{T_y(i)} \mu\left(T_y(i)\right) dT_y} \tag{10}$$

This study utilized MATLAB to create the classification model with fuzzy theory. First, it was feasible to define the parameters of the Gaussian membership function using the fuzzy membership functions of the input value. Second, the Mamdani fuzzy inference rules and defuzzification (center-of-gravity method) were applied to obtain classified assessed values. It was then possible to include the regression algorithm using Eqs. (9) and (10). In linear regression, the model specified that the dependent variable, $y_i$, was a linear combination of the parameters. To model $i$ data points, an independent variable output and parameters $a$ and $b_i$ are expressed in Eq. (11) as follows:

$$y_i = a + b_1 y_{\text{output}}(1) + b_2 y_{\text{output}}(2) + b_3 y_{\text{output}}(3) + \ldots + b_i y_{\text{output}}(i) + \varepsilon_i. \tag{11}$$

Hence, using Eq. (11), the fuzzy regression algorithm was introduced into the repetitive control system, as shown in Fig. 3.

The developed fuzzy regression models with different classifications and the parameters corresponding to $A_d$, $B_d$, $C_c$, and $D_c$ were computed and listed in Table 1.

## IV. COMPARISON OF DISTURBANCE CANCELLATION

### A. REDUCED PERIODIC ERRORS USING A REPETITIVE CONTROL LAW WITH FUZZY REGRESSION

If an interference frequency exists, it is assumed to be a 2-Hz sine wave with an amplitude of 45 units. The input basis functions are sine and cosine waves at 2 Hz; hence, the output

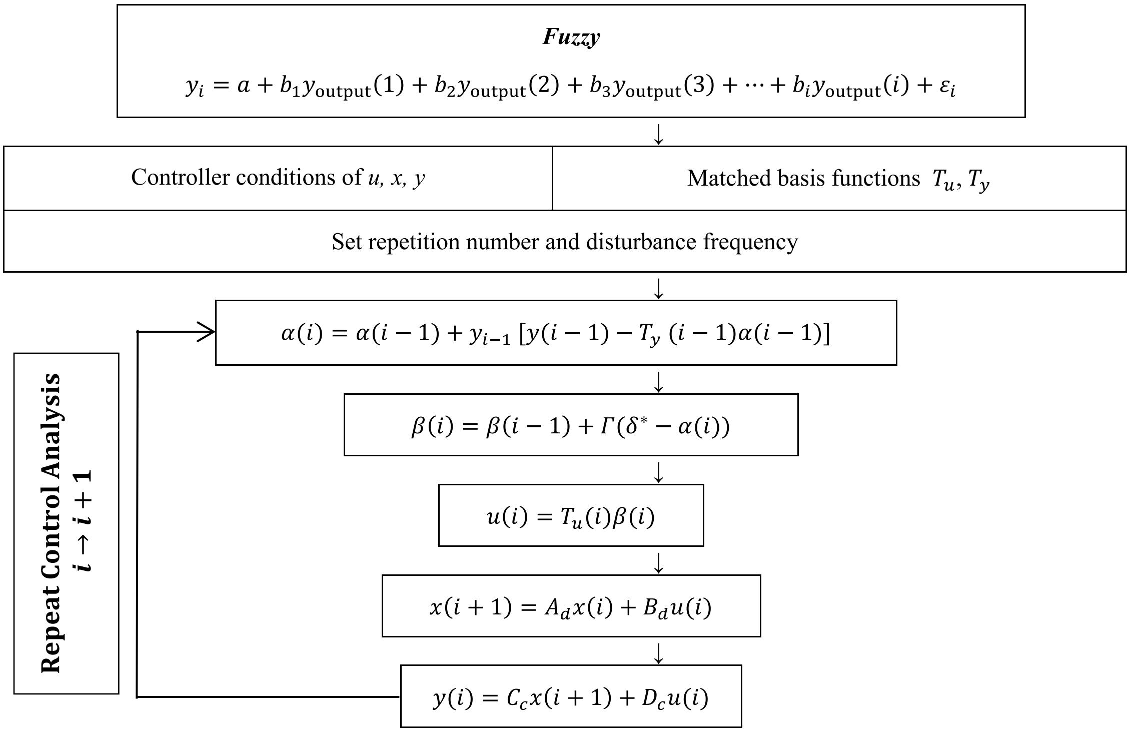


**FIGURE 3.** Fuzzy regression operational flow chart for the system model with linear repetitive control laws, which resembles input-output block diagram of the feedback closed loop control system with the proposed technique.

**TABLE 1.** Parameters corresponding to $A_d$, $B_d$, $C_c$, and $D_c$ in Fig. 3 using a fuzzy regression approach with data $y_{\mathrm{Output}}(i)$ classified into seven different categories

| Model parameter | $A_d$ | $B_d$ | $C_c$ | $D_c$ |
|---|---|---|---|---|
| No classification | 0.63 | 23.41 | 0.82 | 22.96 |
| Two categories | 0.63 | 33.38 | 0.81 | 24.61 |
| Three categories | 0.60 | 79.16 | 0.80 | 32.96 |
| Four categories | 0.61 | 13.48 | 0.79 | 52.96 |
| Five categories | 0.60 | 93.24 | 0.81 | 42.68 |
| Six categories | 0.62 | 43.29 | 0.82 | 62.95 |
| Seven categories | 0.62 | 47.12 | 0.82 | 45.24 |

basis functions are related to the steady-state response. The learning gain, $\Gamma$, is 0.01 times the identity matrix, and the initial $\delta$ and $\beta$ are zero.

For performance analysis, it is suggested to highlight by showing the changes for any variation / combination / configuration of controller and disturbances parameters. Disturbance cancellation uses the fuzzy regression approach to present and describe the filtering results listed below, where repetition of the time-stepped data with classification in the repetitive control process obtains tracking errors with their convergence values, as follows:

1. No classification: The results are shown in Fig. 4. Repeated 56 times, and a convergence value of $10^{-13.53}$.
2. Two categories: The results are shown in Fig. 5. Repeated 55 times, and a convergence value of $10^{-13.69}$.

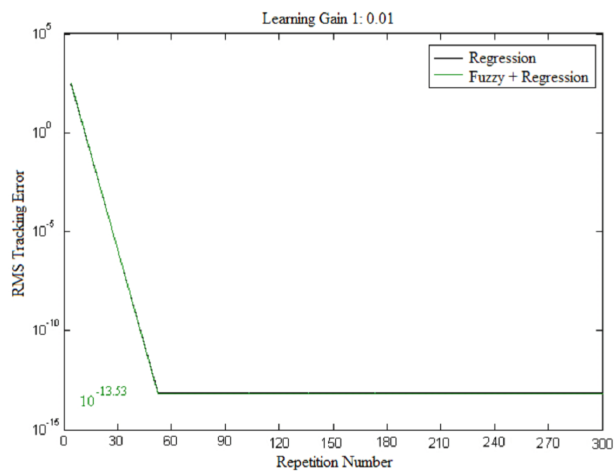


**FIGURE 4.** RMS tracking error: When the fuzzy regression method is used, only 2-Hz basis functions are used for repetitive feedback control, and a sinusoidal interference occurs at 2 Hz (data without classification).

3. Three categories: Repeated 93 times, and a convergence value of $10^{-13.90}$.
4. Four categories: The results are shown in Fig. 6. Repeated 74 times, and a convergence value of $10^{-14.09}$.
5. Five categories: Repeated 75 times, and a convergence value of $10^{-13.97}$.
6. Six categories: The results are shown in Fig. 7. Repeated 65 times, and a convergence value of $10^{-13.74}$.

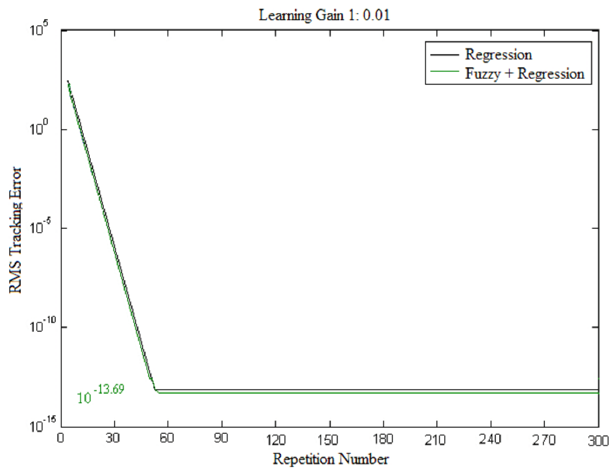


**FIGURE 5.** RMS tracking error: When the fuzzy regression method is used, only 2-Hz basis functions are used for repetitive feedback control, and a sinusoidal interference occurs at 2 Hz (data with two categories).

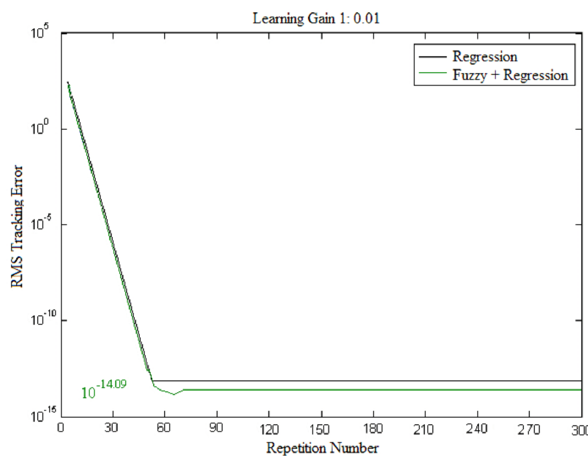


**FIGURE 6.** RMS tracking error: When the fuzzy regression method is used, only 2-Hz basis functions are used for repetitive feedback control, and a sinusoidal interference occurs at 2 Hz (data with 4 categories).

7. Seven categories: Repeated 67 times and a convergence value of $10^{-13.71}$.

Fig. 8 shows the results for every variety of data classification used in this study. It is observed that data classified into four categories shows the most effective convergence value, although the number of repetitions significantly exceeds that of the others. In comparison with the reference [28], the controller performance of this approach has more tracking error reduction and shorter transient response. However, the developed controller in this study has longer computational time used for dividing data for real time applications. Fig. 9 shows the transient response of the output. The response curve (data with 4 categories) is stably converged [28].

### B. COMPARISON OF VERIFICATION AND PREDICTION ERRORS

Next, verification and prediction errors for the linear control models were compared to compute the average effects of data

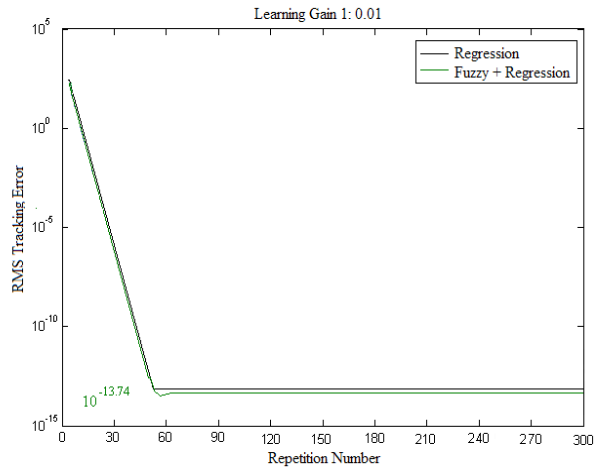


**FIGURE 7.** RMS tracking error: When the fuzzy regression method is used, only 2-Hz basis functions are used for repetitive feedback control, and a sinusoidal interference occurs at 2 Hz (data with 6 categories).

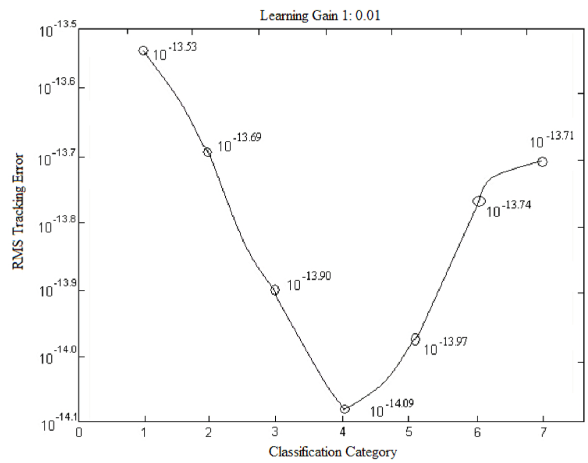


**FIGURE 8.** RMS tracking error: When the fuzzy regression method is used, only 2-Hz basis functions are used for repetitive feedback control, and a sinusoidal interference occurs at 2 Hz (comparison of results with data classified into various categories).

classification on the system output error and to further predict the average performance of the controlled system [26]. A total of 287 data points were counted. The first 200 data points were used as training data to create the verification model, with classifications ranging from one to seven categories, while the remaining 87 data points were used as the prediction data to construct the prediction model. For each classified system, multiple regression analyses were conducted to obtain related models with average errors.

Tables 2 and 3 illustrate the comparison results and demonstrate the verification and prediction error for linear models with up to seven different data categories. The optimal result was verified with data that were divided into four categories, with an average error of 2.71% and a corresponding prediction error of 3.86%. The prediction error obtained the lowest average value of 3.43% when the data was classified into two categories. When the data were divided into seven categories,

**TABLE 2. Comparison of verification errors for linear models with data classified into seven different categories.**

| Category type | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Average error |
|---|---|---|---|---|---|---|---|---|
| No classification | 4.13% | | | | | | | 4.13% |
| Two categories | 3.63% | 4.06% | | | | | | 3.85% |
| Three categories | 3.24% | 3.37% | 2.39% | | | | | 3.00% |
| Four categories | 2.91% | 3.08% | 2.51% | 2.33% | | | | **2.71%** |
| Five categories | 3.08% | 2.81% | 2.77% | 2.71% | 2.64% | | | 2.80% |
| Six categories | 3.06% | 2.88% | 2.79% | 2.37% | 2.89% | 2.91% | | 2.82% |
| Seven categories | 3.19% | 2.90% | 2.86% | 2.55% | 3.04% | 4.01% | Fail | |

**TABLE 3. Comparison of prediction errors for linear models with data classified into seven different categories.**

| Category type | 1 | 2 | 3 | 4 | 5 | 6 | 7 | Average error |
|---|---|---|---|---|---|---|---|---|
| No classification | 4.09% | | | | | | | 4.09% |
| Two categories | 3.32% | 3.54% | | | | | | 3.43% |
| Three categories | 2.93% | 3.77% | 3.84% | | | | | 3.51% |
| Four categories | 3.08% | 3.63% | 3.72% | 5.01% | | | | **3.86%** |
| Five categories | 3.18% | 3.11% | 3.12% | 3.51% | 9.83% | | | 4.55% |
| Six categories | 3.13% | 3.19% | 3.63% | 3.45% | 4.07% | 12.47% | | 4.99% |
| Seven categories | 3.31% | 4.03% | 3.37% | 3.21% | 3.79% | 4.35% | Fail | |

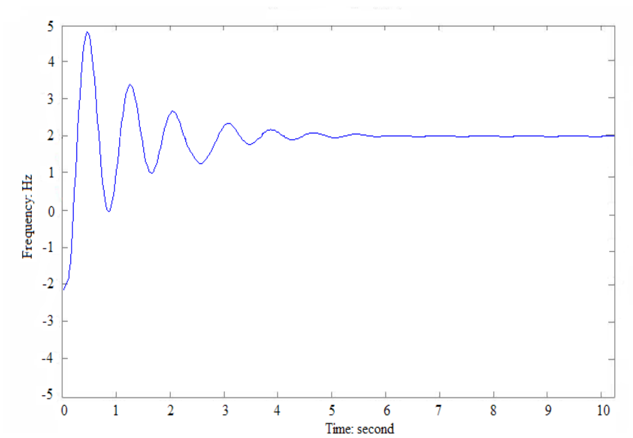


**FIGURE 9.** **The response curve (data with 4 categories).**

insufficient data led to failure as illustrated in Table 2 and Table 3; hence, it was found not to be suitable for data analysis. This applies to the data divided into more than seven categories.

## V. CONCLUSION

In this study, two repetitive control mechanisms were proposed to eliminate the effects of repeated disturbances in the feedback control system and the tracking errors in the feedback controller executing periodic commands. Examples have shown that the proposed method effectively eliminated periodic interference, especially for improving an electron beam focus. The proposed fuzzy regression approach was based on data preprocessing using fuzzy inference rules. The fuzzy theorem approach adopts a Gaussian membership function for system output variables owing to uncertainties that arise from modeling errors, environmental noise, etc. It is determined that the repetitive control process based on data classification with a fuzzy regression approach is more effective than using a pure regression approach. Although the convergence rate was slightly reduced, the accuracy improved. The errors obtained from models constructed with both classified and unclassified data indicated that the data classification system successfully reduced tracking errors. More data classification led to better accuracy, but accuracy decreased when the number of classifications continued to increase. When the data reached a steady-state response or convergence, an optimal convergence value tracking error of $10^{-14.09}$ was obtained, with the data classified into four categories. In comparison with the reference [28], the controller performance of this approach has more tracking error reduction and shorter transient response. Among the verification models, the lowest error was observed for the linear model constructed with data classified into four categories. The average verification error was 2.71%. Among the prediction models, the lowest error was observed for the linear model constructed with data classified into two categories. The average prediction error was 3.43%. Hence, this study provides useful suggestions for future research, with appropriate verification and prediction models using a fuzzy linear series function that can be replaced by a nonlinear power series function. Special thanks are due to Dr. P. F. Shen, Dr. C.-W. Huang and Dr. H.-P. Wen for running related simulations.

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