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Optimization signal writing with machine learning assisted control

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ABSTRACT

The high-precision signal writing machine, experiencing a 0.1% failure rate due to discrete fourier transform (DFT) of position error signal (PES) exceeding control limits, can be improved with an appropriate controller gain. This paper combines machine learning (ML) classification and controller optimization to determine the suitable gain for the hard disk drive (HDD) signal writing process. The result from machine classification has a high potential for position error improvement, distinguishing them from those with obvious degradation. The identified machine classes with high potential for signal write quality improvement undergo controller optimization using a genetic algorithm (GA). The objective function considers gain crossover frequency, phase margin, and PES DFT at low frequencies. Experimental results demonstrate that the new controller gain enhances signal write quality of class 0 and class 3 by 14.68% and 17.18%, respectively, leading to a reduced failure rate down to 0.05%.

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1. INTRODUCTION

The precise control of hard disk drive (HDD) demands high-precision movement [1], [2]. The HDD signal writer, which writes tracks to identified locations on the disk, employs a proportional integral derivative (PID) type controller that undergoes fine-tuning by expert designers using high-performance machines to handle actuator resonances, vibration rejection, and command following before deployment to manufacturing [3]. While PID controllers are commonly used, continuous and prolonged use can lead to errors in the components of the signal writer. Currently, skilled experts are employed to diagnose and identify the causes of abnormalities in the HDD signal writer in order to categorize them for repair. Some machines with improvement potential can reduce positional errors by optimizing controller gain. However, this process is time-consuming in large-scale manufacturing, as machines requiring maintenance and optimization are mixed in with production. Therefore, artificial intelligence-based classification systems and optimization systems must work together to address the problem effectively.

Artificial neural networks (ANN) are employed in various classification applications, including classifying HDD signal writing machine performance. This classification uses operating parameters as features and the symptom of position signal error movement as the label. Machines are classified into four groups: Groups 1 and 2 are earmarked for maintenance due to obvious internal damage, while Groups 0 and 3 are considered for controller optimization [4]. These findings align with past studies on classifying failures in high-speed auto core adhesion mounting machines [5] and mounting head degradation classification [6].

Another important task is PID controller tuning, which can restore performance in drives that have degraded in position movement. Several well-known methods for assessing the robustness and performance of PID controllers in both the frequency and time domains are discussed and compared [7], [8]. The MATLAB GUI-based tuning methods, which work with several techniques, have demonstrated effective performance in motor speed control [9]. Among these methods are the process reaction curve and ultimate sensitivity method. These methods are valued for their speed, simplicity, and avoidance of complex calculations, making them effective for initial PID tuning and preventing instability. They are often benchmarks for other PID tuning techniques due to their reliability [10]. The gradient descent search method is also utilized in PID tuning for quadrotors. This method demonstrates no overshoot, zero steady-state error, and short settling and rise times in evaluation results. However, since it involves online controller tuning, selecting the initial controller gain and learning rate is crucial to avoid local minima and prevent instability [11].

Another approach is tuning PID controllers with particle swarm optimization (PSO), used in an unmanned aerial vehicle (UAV) camera position control. As an evolutionary algorithm, PSO requires evaluating all population members, making initial parameter settings crucial for optimizing search time and tuning effectiveness [12]. Another tuning technique is PID tuning with fuzzy logic, used for temperature control. While it results in longer rise and settling times compared to the Ziegler-Nichols method, it provides a response without overshoot, which is crucial to avoid material disqualification due to overshoot [13]. This method seeks to optimize PID controller gain by deriving equations for open-loop amplitude ratio and phase shift through frequency analysis to meet robustness and performance criteria. However, it is limited in online applications and requires significant expertise to adjust controller gains when system characteristics change [14], consistent with studies on first-order models [15]. Due to mathematical complexity, genetic algorithms (GA) are commonly used in continuous stirred tank reactor (CSTR) processes. The objective function combines integral squared error (ISE), integral absolute error (IAE), integral of time-weighted absolute error (ITAE), and their weighted sum to effectively reject disturbances quickly [16]. PID tuning for a third-order system using a GA is demonstrated, where the error is set as the objective function. High performance in terms of rise time, settling time, and overshoot is observed [17]. The work on motor speed control was shown through simulations and a comparison of the MATLAB PID Tuner app with GA [18].

The introduction of an improved version of the multi-objective function search in the GA known as non-dominated sorting genetic algorithm (NSGA) II is a noteworthy contribution. This algorithm incorporates fast non-dominated sorting, crowding distance, and an elitist mechanism, contributing to its efficiency and effectiveness in handling complex optimization problems. The NSGA II method has been extensively evaluated across a spectrum of linear and non-linear problems, consistently demonstrating promising results. Its robust performance and ability to address diverse multi-objective scenarios make it a widely adopted tool in the field of GA [19], [20]. NSGA-II has been used for PID tuning in various systems, including an automatic voltage regulator (AVR) system, to optimize voltage and current regulation. The objective functions consisted of several combinations to minimize error in ITAE, settling time, overshoot, and damping ratio [21]. Multi-objective optimization with NSGA-II was also applied to minimize torque motion and position deviation during robot movement [22].

Additionally, NSGA-II has been used in UAV navigation systems to minimize error, overshoot, and tuning time [23]. In HDD manufacturing, NSGA-II optimizes key objectives such as position error signal (PES), gain margin, phase margin, crossover frequency, and peak sensitivity. Built on PES data from numerous drives, this method effectively handles complex, large-scale optimization problems [24]. The combination of sensitivity loop shaping and adaptive nonlinear compensation. Leveraging the Kalman–Yakubovic–Popov (KYP) lemma is presented, it aims to reject disturbances with known frequencies while introducing adaptive nonlinear compensation to address low-frequency disturbances, ultimately improving positioning accuracy in the HDD control system [25]. An adaptive multirate control design is proposed to improve performance despite variations in plant gain, ensuring good system performance with uncertain parameters [26]. Additionally, an optimal multirate control design is introduced, which further boosts robustness and stability [27]. A nonlinear time-varying unified control scheme (UCS) is proposed for achieving fast and smooth track-seeking and track-following in HDD. This scheme aims to avoid the problem of mode switching and demonstrates a significant improvement in performance and robustness [28].

Even though quantitative analysis of controller tuning can compensate for plant variations, handling machines with significant damage that require maintenance remains challenging and often leads to wasted optimization efforts. Additionally, some machines with potential for improvement exhibit unique characteristics, and a single set of controller gains cannot effectively minimize position errors. This paper proposes a solution involving grouping machines based on their behavior using ANN and employing controller gains obtained from offline GA optimization. This method aims to reduce signal writing failures within time constraints by using machine learning (ML) to select the appropriate controller gain from GA, while also classifying machines needing repair and providing guidelines to enhance maintenance efficiency.

2. METHOD

This section introduced the machines targeted for performance improvement and outlined the method employed to determine the appropriate PID controller gain for each machine class. The machines under consideration varied in their operational parameters, which required tailored tuning strategies. The selected method ensured that the PID controller gain was optimized to enhance stability and responsiveness across different machine types.

2.1. Signal write machine

The machine used in this research was an HDD signal writer, with the control diagram illustrated in Figure 1, It consisted of the PA2000 positioner model, which integrated a voice coil motor (VCM) with an absolute encoder to control the HDD arm movement and ascertain its position, and an SA200 amplifier linked to receive control signals from a closed-loop control system. The focus of this paper was on two blocks in the position control: the first block, highlighted in orange, involved optimizing the controller gain, while the second block, indicated in blue, involved using ML to assist with gain selection.

The mathematical model of the signal writing machine, represented by the red block, was estimated using a system identification technique. The model structure comprised a standard second-order form at low frequencies and complex poles and zeros at high frequencies, as represented by (1). The parameters for both continuous and discrete models were provided in [4].

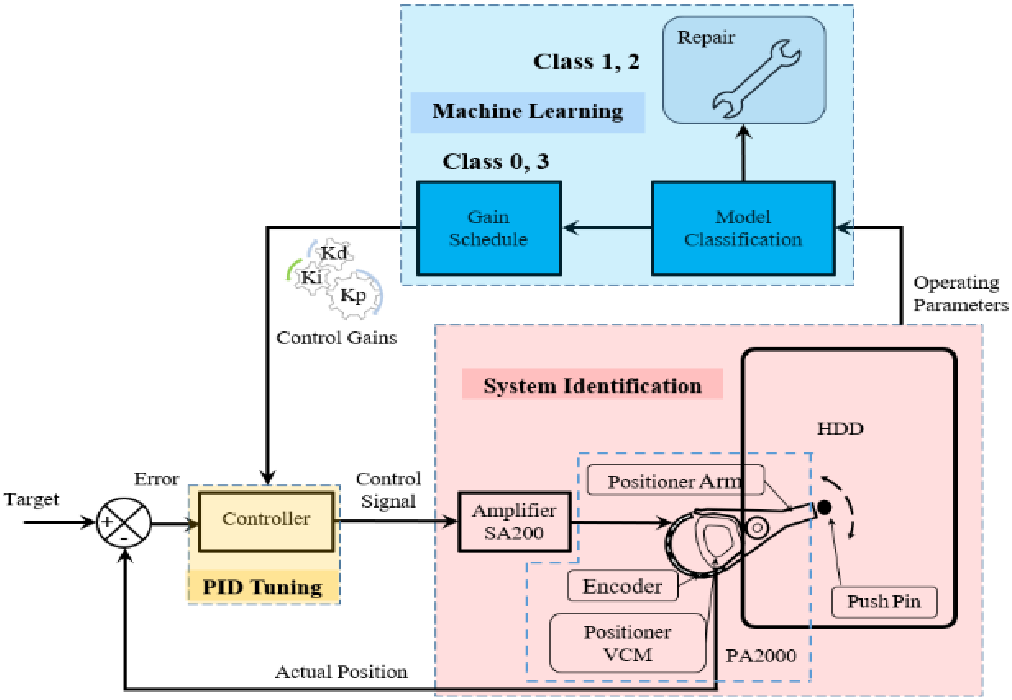
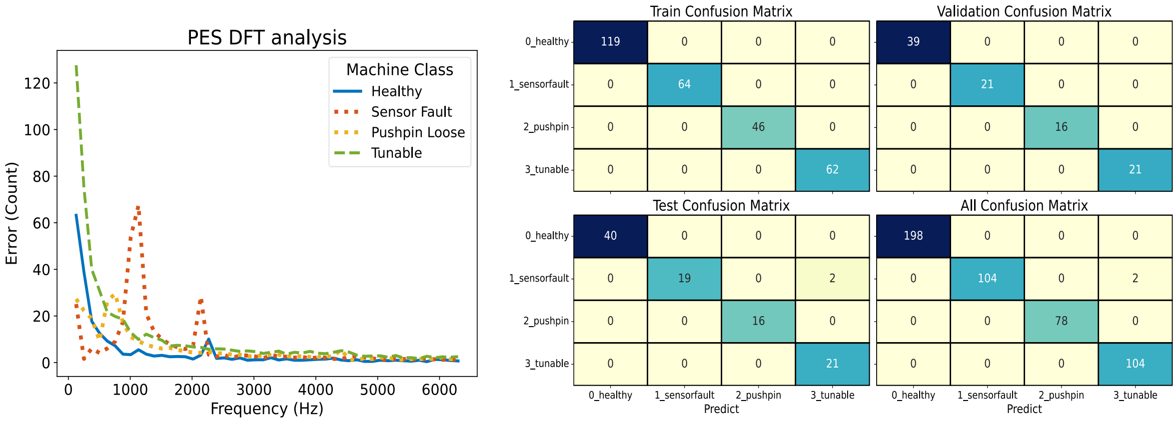


Figure 1. Position control of signal writer machine

$$G(s) = e^{(-t_d \times s)} \times \frac{k_{dc}\omega_0^2}{s^2+2\zeta_0\omega_0 s+\omega_0^2} \times k_{res} \times \prod_{r=1}^{N} \frac{s^2+2\zeta_{nr}\omega_{nr}s+\omega_{nr}^2}{s^2+2\zeta_{dr}\,\omega_{dr}s+\omega_{dr}^2} \tag{1}$$

where k_{dc} is the low frequency DC gain
ω_0 is the natural frequency
ζ_0 is the damping ratio
t_d is the delay time
k_{res} is the high frequency resonance gain
ω_{nr} is the resonance zeros frequency
ω_{dr} is the resonance poles frequency
ζ_{nr} is the resonance zeros damping ratio
ζ_{dr} is the resonance poles damping ratio
N is the number of resonance peaks

The current symptoms of machine failure related to position movement errors and the potential classification system using an artificial neural network (ANN) were presented in Figure 2. The analysis of machine characteristics in the frequency domain was conducted by transforming the PES from the time domain to the frequency domain using the discrete fourier transform (DFT), as illustrated in Figure 2(a). Class 1, depicted by the orange dotted line, was observed to exhibit two high peaks at approximately 1,100 Hz and 2,200 Hz. Meanwhile, Class 2, also represented by a yellow dotted line, was observed to display a lower amplitude between 600 and 900 Hz. The maintenance background indicated that Classes 1 and 2 exhibited clear degradation in machine components (voltage drop in the encoder sensor for Class 1 and loose push pin for Class 2), which necessitated prompt maintenance. Conversely, Classes 0 and 3, represented by the blue line and green dashed line, respectively, were shown to follow similar patterns but differed in amplitude levels across frequencies. Class 3 demonstrated higher amplitude values compared to Class 0, suggesting a greater impact from low-frequency vibrations. It was found that the existing controller gain was insufficient for effectively eliminating these errors. ML, specifically using an ANN, was employed to identify machine class symptoms, with the classification results depicted in Figure 2(b). It was noted that two data points from Class 1 might have been misclassified during the optimization process; however, this discrepancy was deemed to have a relatively minor impact on the overall results.



(a) (b)

Figure 2. Machine failure symptom (a) machine analysis by DFT and (b) machine classification by ANN

Table 1 presented the defects and failure rates related to position errors for each group. Class 0 performed well with zero defects. In contrast, Classes 1 and 2 exhibited higher failure rates, exceeding 30%. The defects, which were difficult to identify visually, included low voltage from the encoder sensor in Class 1 and loose push pins in Class 2. To prevent these two classes from generating failure rates exceeding 30%, internal monitoring was implemented. If three out of ten drives failed, the tester was designed to shut down automatically and required maintenance by skilled experts.

For Class 3, no defects were identified, but intermittent failures related to position movement error were observed, with a failure rate of less than 30%. The shutdown monitoring system was found to be inadequate for this group. It was indicated by laboratory testing that performance could be restored by adjusting the controller gain through a design of experiments approach, which involved multiple experiments and the use of response surface methodology to find optimal gains. The trend of the new optimal gain was found to increase Ki. Although the implementation of this technique was found to be time-consuming and labor-intensive due to the large scale of manufacturing, it was suggested that Class 3 still had potential for improvement in reducing position error.

Despite no failures being produced by Class 0, potential for further reduction in position errors remained due to its high performance. Therefore, new optimal gains, distinct from those used in other classes, were recommended. To reduce the number of experiments, a GA was employed to determine the optimal solutions for both classes.

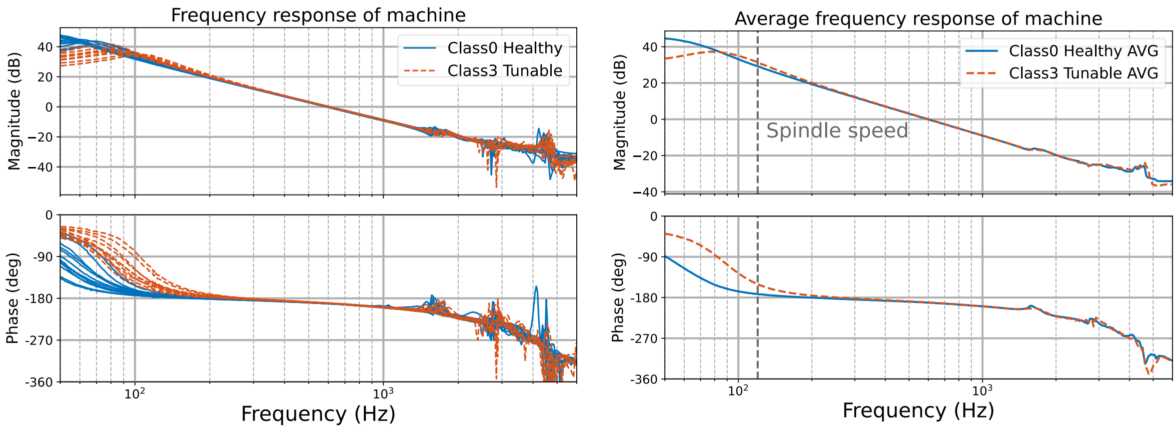
Table 1. Failure rate and defect parts

Machine class	Failure rate (%)	Defect part	Action
Class0	0	Healthy	Improve PES
Class1	>30	Low encoder sensor voltage	Repair
Class2	>30	Pushpin loose	Repair
Class3	<30, intermittent	No defect found, Tunable	Require controller tuning

2.2. Genetic algorithm (GA)

A GA was an evolutionary optimization method inspired by natural selection and genetics. A population of potential solutions was evolved through selection, crossover, and mutation to iteratively approach optimal solutions. To solve multi-objective problems, simple methods were used, which involved combining objectives using predefined weighting vectors. Another solving method, Pareto fronts, formed the basis of the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). NSGA-II employed non-dominated sorting, crowding distance, and elitism to maintain diversity and meet specified criteria. NSGA-II was used in this research, implemented in MATLAB, to determine the optimal controller gains for Class 0 and Class 3 machines, as classified by an ANN.

In model-based controller tuning, a precise model was required. The mathematical models were derived from the frequency response data shown in Figure 3. The actual responses of machines in classes 0 and 3 were collected by injecting a sine sweep from 50 to 6,000 Hz at the input point before being servo amplified. Position movement was collected in the time response at each frequency and transformed into a frequency response, as shown in the Bode plot in Figure 3(a). The blue line represented Class 0, which had the potential to find a new optimal gain, while the orange line indicated Class 3, which required tuning. The average values at each frequency point were presented in Figure 3(b). As expected, the average model for Class 3 clearly indicated a high potential for vibration impact from the spindle motor speed at 7,200 rpm (120 Hz), which could lead to significant oscillations in the time response.



(a) (b)

Figure 3. Frequency response function (a) class 0 and 3 data and (b) average of class 0 and 3

2.3. GA configuration

The objective function of this study was a multi-objective function that combined the gain crossover frequency at 550 Hz, phase margin at 40 degrees, and the minimum PES DFT value at low frequencies, as shown in (2).

$$obj = min\big(abs(XFreq - 550)\big), \mathrm{min}\big(abs(haseMargin - 40)\big), \mathrm{min}(PES\ DFT) \tag{2}$$

In the optimization process, setting the initial values was crucial. Improper initialization, such as not limiting the range of the controller gain, was found to lead to system instability, as illustrated in Figure 4. To address this issue, the root locus or Routh-Hurwitz method was employed to determine the gain range necessary to maintain system stability. Since the signal writing machine already had a conventionally stable controller gain, this gain was used as the starting point to prevent instability and ensure quick convergence to an appropriate solution. The Kp, Ki, and Kd gains were offset by ±20%, ±100%, and ±30%, respectively, from their original values. The original values for Kp, Ki, and Kd were 6000, 200, and 2800, respectively.

The initial values and objective function were performed as following details.

Kp lower / upper limit:	4800 to 7200 DAC	Pareto front:	16 solutions
Ki lower / upper limit:	100 to 400 DAC	Crossover rate:	100%
Kd lower / upper limit:	2240 to 3640 DAC	Mutation rate:	10 %
Number of bit:	16 bits	Generation:	1000 Gens

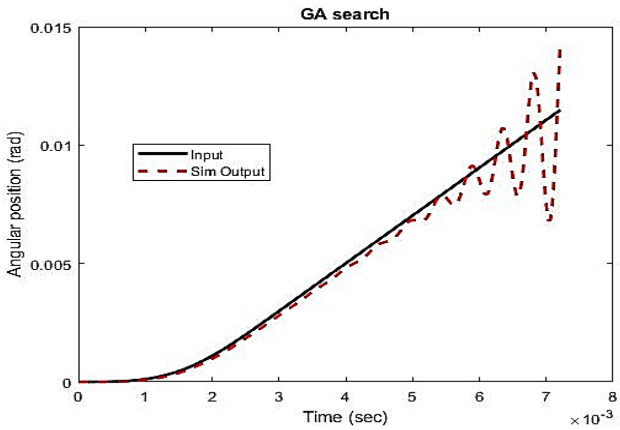
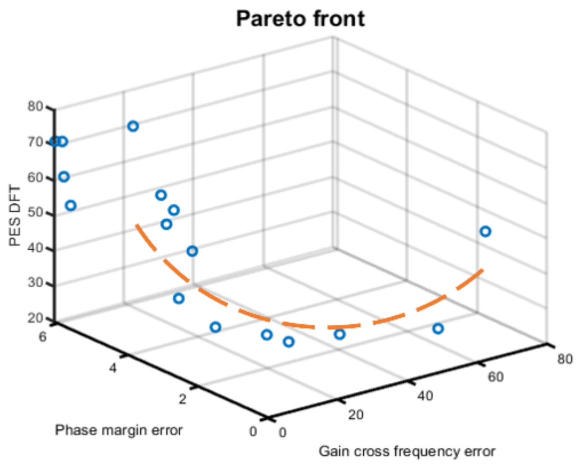
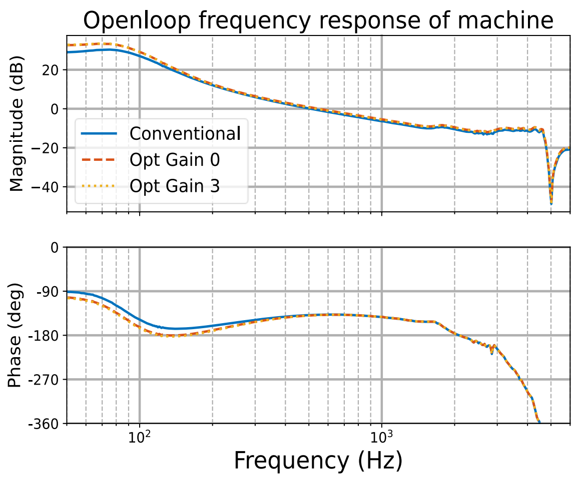


Figure 4. Unstable system from improper gain

The GA search results were shown in Figure 5. The 16 solutions from the search results for Class 3 were presented in Figure 5(a). The selection of the optimal gain solution was based on the solution that provided the minimum PES DFT result while maintaining the closest gain crossover frequency and phase margin. The comparison of the open-loop frequency response between the conventional gain and the newly optimized gains was shown in Figure 5(b). It was evident that both new gains increased the magnitude to meet the gain crossover frequency and phase margin, which were objectives in the frequency domain. Specifically, the low-frequency response was increased due to Ki, resulting in the elimination of errors at the closed-loop steady state in the time domain, this result was strongly correlated with the design of experiments approach, which utilized the response surface methodology.

The final results of the gains obtained during the search, which met the objective function of manufacturing criteria for both time and frequency response, were presented in Table 2. They exhibited a trend of overall increase, suggesting that the machine could operate faster than normal for both machine classes. The Kp gain for Class 0 was found to be slightly higher than that for Class 3, strongly indicating that Class 0 was able to produce a low position error while maintaining frequency response criteria. Nevertheless, there was still room for Class 3 to reduce position error by increasing the Kp gain to a suitable level.





(a) (b)

Figure 5. GA search result (a) 3 objectives in class 3 and (b) openloop response of class 0 and 3

Table 2. Summary of PID gain search result

Controller	Kp (DAC)	Ki (DAC)	Kd (DAC)
Conventional	6000	200	2800
Opt. Class0	6597	331	3147
Opt. Class3	6450	340	3088

3. RESULTS AND DISCUSSION

When GA-derived gains were applied to Class 0 and Class 3 machines, their performance was evaluated through frequency and time response analyses. This evaluation highlighted the impact of optimized controller settings on the behavior of the signal writer machine. The open-loop frequency response analysis examined the gain crossover frequency and phase margin, while the time response analysis focused on the closed-loop PES.

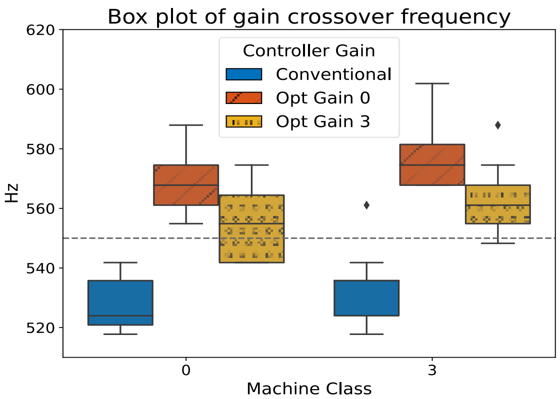
3.1. Open loop frequency response

Figure 6 illustrated two key frequency response parameters: gain crossover frequency and phase margin. The gain crossover frequency indicated where the system's open-loop transfer function magnitude equaled 1 (0 dB), while the phase margin was the difference between the phase angle at this frequency and negative 180 degrees. Both parameters were critical for evaluating the transient response and stability.

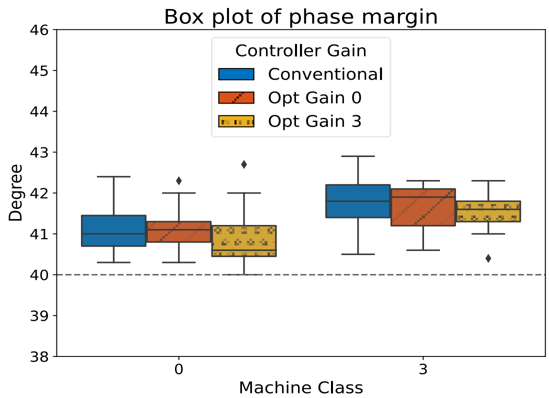
Figure 6(a) demonstrated that GA-derived gains (in orange and yellow) significantly increased the gain crossover frequency towards the target of 550 Hz. For Class 0, it rose from 527 to 567 Hz, and for Class 3, it increased from 534 to 564 Hz. The increase in gain crossover frequency, observed with the new gains, was correlated with a higher closed-loop bandwidth and a faster response compared to conventional gains.

Figure 6(b) showed that GA-derived gains slightly decreased the phase margin to the target of 40 degrees but did not significantly differ from conventional gains, indicating similar levels of stability for each machine group. The combination of an increased gain crossover frequency with a slight change in phase margin suggested that the machine could achieve a faster transient response while maintaining the same stability level.

Additional testing revealed that swapping controllers between Class 0 and Class 3 resulted in frequencies that remained higher than with conventional gains. Class 0 had a gain crossover frequency of 567 Hz, while some Class 3 machines exceeded 601 Hz. Implementing Class 0 gains in Class 3 machines was advised against due to increased sensitivity to spindle motor vibrations and high-frequency resonance.



(a)



(b)

Figure 6. Frequency response (a) gain crossover frequency and (b) phase margin

3.2. Closed loop time response

Figure 7 illustrated the movement errors during the signal writing process from the outer to the inner part of the disk. It was shown in Figure 7(a) that the spiral PES, influenced by the newly applied GA-derived gains, exhibited a reduced overshoot of position error during initial movements.

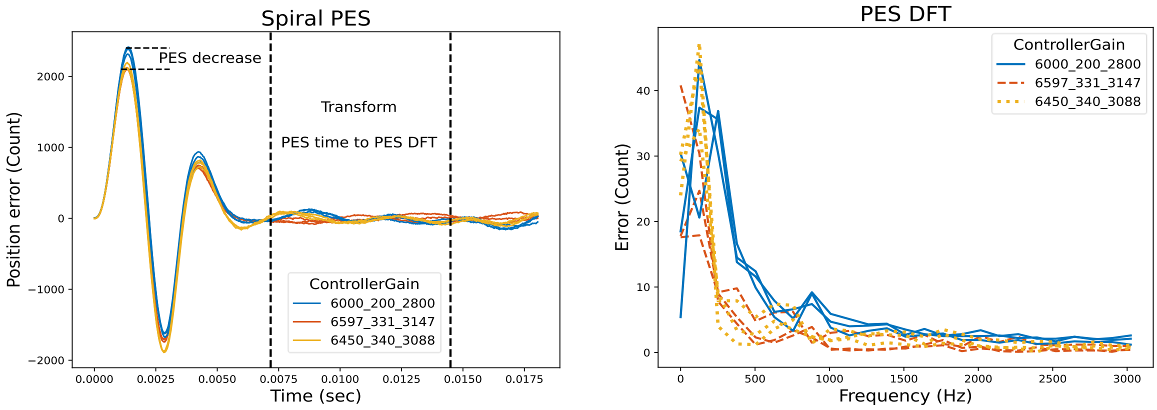
The 200 data points used to assess movement quality, indicated by the vertical dashed line, were not clear in the time domain. Therefore, the spiral PES was transformed from the time domain to the frequency domain using the DFT, (X_k), as described in (3). Only the amplitude component defined by (4), was considered (ignoring the phase component). The overall amplitude of the harmonic at each frequency was calculated, with the results shown in Figure 7(b). Notable improvements were clearly shown, especially at lower frequencies starting from 400 Hz.

It was inferred that the system with GA-derived gains was capable of eliminating position errors more rapidly compared to conventional gains. This was further supported by the gain crossover frequency objective function, where the high gain crossover frequency indicated the potential to increase system bandwidth, resulting in a faster system response.

$$X_k = \sum_{n=0}^{N-1} x_n \left[\cos\left(\frac{2\pi kn}{N}\right) - i.\sin\left(\frac{2\pi kn}{N}\right)\right] \quad (3)$$

where n is the current sample
k is the current frequency, where k ∈ [0, N −1]
x_n is the sine value at sample n
N is the number of samples?

$$amp(k) = \frac{\sqrt{real(X_k)^2 + imaginary(X_k)^2}}{N} \quad (4)$$



(a) (b)

Figure 7. Position movement error (a) spiral movement error in time and (b) DFT of spiral PES

3.3. Hypothesis test

When additional DFT data were collected from machines in both Class 0 and Class 3 using the new PID gains from GA, the representative PES in the 600 to 1,500 Hz range was calculated using the Euclidean distance, as shown in (5), Figure 8 compared the performance of the GA gains, with blue representing conventional gains, orange representing PID gains for Class 0, and yellow representing PID gains for Class 3.

$$DFT_{Low} = \sqrt{amp_{600Hz}^2 + \cdots + amp_{1500Hz}^2} \quad (5)$$

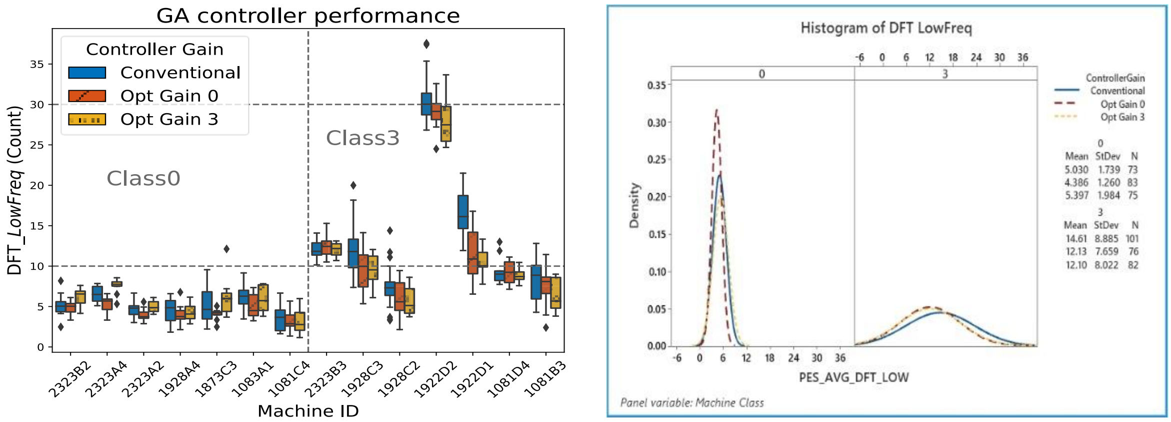
For machines in Class 0, Figure 8(a) shows that both new PID gains perform well, with DFT values below 10 counts, except for machine 1873C3, which exhibits an upper outlier with the PID gain from Class 3. Figure 8(b) reveals that the smallest mean DFT is 4.386 counts, with a low standard deviation of 1.260 counts. This supports observations from the open-loop response, where both new gains have improved the system's speed in eliminating errors. The GA-derived gain for Class 0 yields the best results for this machine group.

For machines in Class 3, Figure 8(a) shows several scenarios with detailed explanations:

Machine 1922D2: This machine showed significant improvement in failure rates. Conventional gain resulted in DFT median values exceeding 30.66 counts. By using the new gains, the median value was reduced to 27.92 counts with Opt 0 gain and to 25.27 counts with Opt 3 gain, thus reducing manufacturing failure rates. Machine 1928C3, 1928C2, 1922D1, 1081B3: These machines also performed well with both gains, with the Opt 3 gain providing the best performance. Machine 2323B3, 1081D4: These machines exhibited optimal performance only with the Class 3 gain. The use of the Class 0 gain resulted in increased errors, likely due to the higher gain crossover frequency observed in the open-loop frequency response, which amplified noise and vibrations from the spindle motor. Consequently, the Class 0 gains were avoided for these machines.

Figure 8(b) demonstrated that the PID gain for machines in Class 3 performed as expected, with a DFT of 12.10 counts and a low standard deviation of 8.022 counts. The GA-derived gain for Class 3 yielded the best results for this machine group.

Due to the small sample size in the evaluation, a two-sample T-test was conducted to validate the improvements. Table 3 demonstrated that the T-test results yielded T-values of -2.62 and -2.01, with P-values of 0.005 and 0.023 for Class 0 and Class 3, respectively, both of which were below 0.05. The null hypotheses for both classes were rejected, and the alternative hypotheses were accepted. This indicated that the new controller gains significantly reduced the mean DFT compared to the conventional gain.



(a) (b)

Figure 8. PES DFT objective (a) data by machine and (b) distribution by machine class

Table 3. Two-Sample T-Test

Class 0			Class 3		
µ1: mean of DFT, Opt0 Gain			µ1: mean of DFT, Opt3 Gain		
µ2: mean of DFT, Conventional Gain			µ2: mean of DFT, Conventional Gain		
Null hypothesis		H0: µ1 – µ2 = 0	Null hypothesis		H0: µ1 – µ2 = 0
Alternative hypothesis		H1: µ1 – µ2 < 0	Alternative hypothesis		H1: µ1 – µ2 < 0
T-Value = -2.62	DF = 129	P-Value = 0.005	T-Value = -2.01	DF = 178	P-Value = 0.023

Tables 4 and 5 summarized the experimental results for the three objectives. The gain crossover frequency was increased by approximately 30 Hz, which expanded the closed-loop bandwidth and led to improved tracking and a quicker response to reference signals, thereby reducing position movement errors. The phase margin remained around 41 degrees, indicating consistent stability, transient response, and disturbance rejection. The signal write quality, measured using DFT of the position error signal, improved by 14.68% for Class 0 and 17.18% for Class 3.

Table 4. Comparison of GA performance in class 0

Mean of parameter	Conventional 6000, 200, 2800	Opt0 6597, 331, 3147	Improvement
Gain crossover frequency (Hz)	527	567	Faster
Phase margin (Degree)	41.12	41.14	Same stability
DFT of PES (Count)	5.03	4.39	14.68%

Table 5. Comparison of GA performance in class 3

Mean of parameter	Conventional 6000, 200, 2800	Opt3 6450, 340, 3088	Improvement
Gain crossover frequency (Hz)	534	564	Faster
Phase margin (Degree)	41.80	41.50	Same stability
DFT of PES (Counts)	14.61	12.10	17.18%

4. CONCLUSION

The failure related to position movement errors in the HDD signal writing process needs to be addressed. While some machines require repairs due to component degradation, others can reduce failure rates by optimizing controller gains to correct movement errors. This paper presents a method that combines classification and optimization to enhance signal writing quality and streamline maintenance, thereby reducing damage diagnosis time and enabling automatic control adjustments for improved efficiency. The study employs an ANN to identify machine groups needing repairs and guide the identification of potential damage parts, as well as machine groups with potential for improvement. Optimal gains are determined using the NSGA II multi-objective function concept, resulting in a 14.68% improvement for the healthy machine class and a 17.18% improvement for the tunable machine class, both statistically significant. The increased gains for both machine classes lead to a rise in gain crossover frequency, nearing the manufacturing criterion, while the phase margin remains relatively unchanged. This indicates that the system can be made faster without compromising stability. Early detection of problematic machines with obvious degradation and improved signal write quality can reduce the error rate in the signal writing process from 0.1% to 0.05% compared to using a single set of controller gains. This concept can be adapted for systems requiring optimization under time constraints. It is recommended that further research be undertaken on machines in class 3 that cannot reduce position errors with new controller gains. This could lead to either further optimization or deeming them irreparable.

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