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Vibration Control in Wind Tunnel by Biologic Neurons Methods

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Abstract

This study presents an innovative approach for vibration control in wind tunnels using a combination of Back-Propagation (BP) neural network and Proportional-Integral-Derivative (PID) control. Wind tunnel testing plays a crucial role in aerodynamic research, but it often faces challenges related to vibrations that can affect the accuracy of measurements. Traditional PID controllers are effective but may struggle to adapt to dynamic and complex vibration patterns. In contrast, BP neural networks offer learning capabilities and adaptability, making them suitable for handling such challenges, also examines the impact of active vibration control with feedback control to reduce or eliminate unwanted vibrations in a system actively with development and experimental evaluation controlled separately by both PID and BP neural network to make comparisons by MATLAB - Simulink software's thorough Laboratory with vibrations in the sting can affect the accuracy and repeatability of the test results, so active vibration control can be used to improve the performance of the wind tunnel. The proposed system integrates a BP neural network with a PID controller to create a robust vibration control mechanism. The BP neural network is trained to learn the dynamic behavior of the wind tunnel system and generate control signals based on input parameters such as setpoints, error signals, and their derivatives. The PID controller works in tandem with the neural network to fine-tune the control signals and ensure stability. The experimental results demonstrate the effectiveness of the proposed approach in suppressing vibrations in wind tunnel testing. The system achieves improved accuracy and stability, leading to more reliable aerodynamic measurements. This research to shows BB neural network vibration control impact and analyze the behaver of K_p, K_i, and K_d.

Keywords: Active sting, vibration control, wind tunnel testing, neural network-driven fractional approach.

1. Introduction

The study investigates active vibration control methods aimed at reducing or eliminating unwanted vibrations in a system. It places a particular emphasis on the "sting," a slender and flexible structure that is used to hold and position models or test pieces during aerodynamic testing in wind tunnels. Considering that vibrations inside the test chamber can affect the precision and reliability of experimental outcomes, implementing active vibration control for the sting is crucial for optimizing the wind tunnel's overall performance. Since vibrations within the test chamber have the potential to compromise the accuracy and consistency of the results obtained from experiments, it is essential to employ active vibration control measures for the sting, to ensure that the experimental results are both precise and consistent, active vibration control of the sting is of utmost importance [1]. Various approaches can be employed for active vibration control, including sensor-based detection of vibrations and the utilization of algorithms to generate control signals aimed at counteracting them. To facilitate the investigation, instrumentation capable of measuring the vibrations of the sting would be necessary.

Following the installation of sensors, experimental setups involving wind tunnel tests with induced gusts or turbulence would be conducted to stimulate the vibrations of the sting. Actuators such as piezoelectric components or shape-memory alloys, capable of rapidly adjusting the shape in response to electrical stimuli, can be utilized to apply these control signals [2]. Achieving an effective balance between performance and stability poses a significant challenge in active vibration control. If the control system is overly passive, it may fail to sufficiently mitigate vibrations, thereby compromising the accuracy of the experimental results. The effectiveness of active sting vibration control relies significantly on the control system's precise design and tuning. In the context of wind tunnel experiments, active vibration control entails the utilization of feedback and control methodologies to actively reduce the vibrations of the sting. The primary objective is to minimize string vibrations, thereby enhancing the precision and reliability of wind tunnel measurements. Implementation methods may Include feedback control with sensors/actuators and passive damping. Typically, in wind tunnel environments, piezoelectric actuators and sensors are employed, enabling real-time detection and correction of vibrations on the sting [3-4].

2. Background and Significance of the Study

The human brain features a vast network of over 100 billion interconnected neurons, with each neuron linking to about 10,000 others, totaling around 60 trillion synaptic connections. Our knowledge of the intricate human brain is limited. Yet, it activates multiple neurons at once during certain actions, outperforming the speed of the fastest supercomputers by a significant margin [5]. The brain, like a complex nonlinear computer, uses neurons for information processing. In the 1940s, McCulloch and Pitts created the initial mathematical neuron model from their fundamental traits.

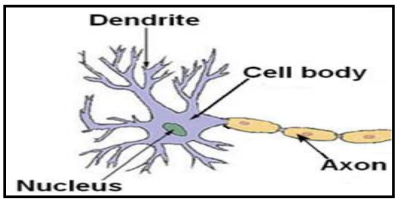


Figure 1 Schematic diagram of biological neurons

Figure 1. depicts a simplified diagram outlining the structure of a biological neuron. Within the human brain, neurons receive electrical input signals via a network of dendrites, these dendrites converge their inputs, with the neuron effectively summing up all incoming signals, prioritizing excitatory input over inhibitory input reaching a threshold, if the sum surpasses a certain threshold, an action potential is generated and transmitted along the neuron's axon. The axon extends into numerous terminal branches, forming connections with dendrites of neighboring neurons.

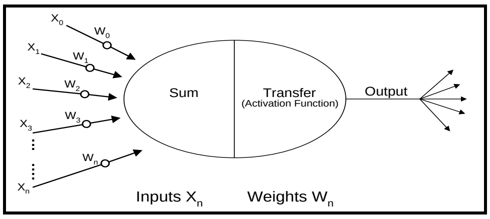


Figure 1 Artificial neuron diagram attempt to simulate this operation

In Figure 2, the signals denoted $(X_0 - X_n)$ represent inputs transmitted to the neuron, accompanied by their corresponding connection weights designated as $(W_0 - W_n)$. These signals embody both inhibitory and excitatory transmissions conveyed along the dendrites. Within the neuron, these inputs undergo summation, followed by the application of a transfer function to generate an output, typically falling within the range of 0 to 1 or -1 to +1.

Individual neurons establish connections with numerous other neurons, exhibiting diverse configurations, creating an artificial neural network, Hebb's theory from the late 1940s posits that learning strengthens biological neurons' connections, optimizing neural pathway efficiency. Artificial neurons mimic learning by adjusting input weights through feedback (Figure 3), enabling continuous weight updates for network stabilization and adaptation across problem domains.

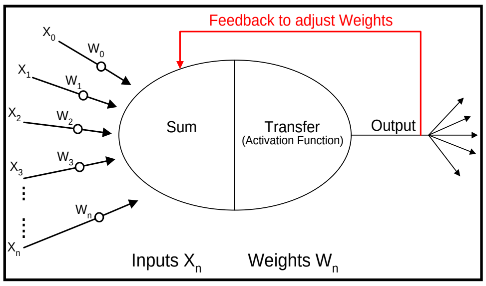


Figure 2 Artificial neurons with feedback

The integration of a Backpropagation (BP) neural network with Proportional-Integral-Derivative (PID) control results in a composite learning algorithm that operates on a hierarchical neural network structure. This structure is composed of an input layer, one or more hidden layers, and an output layer, where neurons are interconnected across these layers [4-6]. When the network is presented with a set of learning patterns, each neuron within the network processes the inputs it receives and calculates the corresponding connection weights. The weights are then modified through an iterative process that starts at the output layer and propagates adjustments back through the hidden layers. The goal of these iterative adjustments is to reduce the error— the difference between the desired output and the current output— to a minimum.

This process of backpropagating errors and updating weights continues in a loop until the total error across the network is driven down to a level that is deemed acceptable, indicating that the learning phase has been successfully concluded. Reformulated, the BP neural network, in tandem with PID control, creates an advanced learning framework within a multi-layered neural network. As learning patterns are input into the system, neurons throughout the network engage in computations that lead to the formulation of connection weights. These weights are iteratively fine-tuned from the output layer backward through the hidden layers, all in the pursuit of error minimization. The iterative optimization continues cyclically until the network's overall error is reduced to a satisfactory threshold, marking the end of the learning cycle.

Traditional PID control often involves an endless array of nonlinear parameter combinations, whereas Backpropagation (BP) neural networks have the flexibility to handle any arbitrary nonlinear expressions. This capability allows BP neural networks to be used for learning and adapting the performance of a system, which in turn can be used to adjust the parameters of a PID controller, such as the proportional gain K_p, integral gain K_i, and derivative gain K_d, in an adaptive manner. A control system that combines a BP neural network-based PID controller with a standard PID controller. This integration allows for real-time tuning of the PID parameters through the neural network, which is used to control the switching of heating elements within a lighting control system. The system operates on a closed-loop principle to maintain consistent illumination levels inside tunnels, aiming to provide the best possible lighting conditions.

For the neural network model, a three-layer BP network configuration is utilized, denoted as (3-8-3), where the input layer takes in M variables represented $Q_j^{(1)} = x(j)\ j = 1,2,\dots,M$. Here, M stands for the total number of input variables fed into the system. A hybrid control approach that employs a BP neural network to dynamically refine the parameters of a conventional PID controller. This integration is particularly useful for adjusting the operation of heating elements in a tunnel lighting system to maintain a steady light level. The neural network, structured with three layers and capable of processing M input variables, is instrumental in this adaptive control strategy.

The formula for calculating the hidden layer is as follows:

$$net_i^{(2)} = \sum_{j=0}^{M} w_{ij}^{(2)} Q_j^{(1)} \quad (1)$$

The $w_{ij}^{(2)}$ of $Q_i^{(2)}(k) = f\left(net_i^{(2)}(k)\right)$ $(i = 1, \dots, Q)$ as the hidden layer weights are calculated using the following equation, with a sigmoid function as the system's activation function [7]:

$$f(x) = \tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{2}$$

$$net_i^{(3)}(k) = \sum_{i=0}^{Q} w_{ij}^{(3)} Q_j^{(2)}(k) \tag{3}$$

$$Q_i^{(3)}(k) = g(net_i^{(3)}(k)) \tag{4}$$

$$Q_1^{(3)}(k) = Kp\ Q_2^{(3)}(k) = Ki\ Q_3^{(3)}(k) = Kd \tag{5}$$

$K_p, K_i\ and\ K_d$ are The three control parameters of the PID controller [8], and the system's activation function is calculated as follows:

$$g(x) = \frac{1}{2}(1 + \tanh(x)) = \frac{e^x}{e^x + e^{-x}} \tag{6}$$

The performance index function of the system is obtained as:

$$E(k) = \frac{1}{2}(\mathrm{rank(k)} - \mathrm{yout}(k))^2 \tag{7}$$

Adding inertia term to accelerate the convergence speed of NN PID system

$$\Delta w_{li}^{(3)}(k) = -\eta \frac{\partial \mathrm{E(k)}}{\partial w_{li}^{(3)}} + \alpha w_{li}^{(3)}(k-1) \tag{8}$$

α is indicative of the inertial properties of the system, which can influence its dynamic behavior, while η reflects the rate at which the system is capable of learning or adjusting its parameters in response to new data or feedback.

$$\frac{\partial \mathrm{E(k)}}{\partial w_{li}^{(3)}} = \frac{\partial \mathrm{E(k)}}{\partial y(k)} \cdot \frac{\partial \mathrm{y(k)}}{\partial u(k)} \cdot \frac{\partial u(k)}{\partial O_i^{(3)}(k)} \cdot \frac{\partial O_i^{(3)}(k)}{\partial net_i^{(3)}(k)} \cdot \frac{\partial net_i^{(3)}(k)}{\partial w_{li}^{(3)}},\ \frac{\partial net_i^{(3)}(k)}{\partial w_{li}^{(3)}} = O_i^{(2)} \tag{9}$$

Among them due to the partial $\frac{\partial \mathrm{y(k)}}{\partial u(k)}$ is unknown, so adopting $sgn(\frac{\partial \mathrm{y(k)}}{\partial u(k)})$ to replace the error through the learning rate to be revised [9]. The calculation formula is available

$$\frac{\partial u(k)}{\partial O_1^{(3)}(k)} = error(k) - error(k-1) \tag{10}$$

$$\frac{\partial u(k)}{\partial O_2^{(3)}(k)} = error(k) \tag{11}$$

$$\frac{\partial u(k)}{\partial O_3^{(3)}(k)} = error(k) - 2error(k-1) + error(k-2) \tag{12}$$

2.1 Literature review

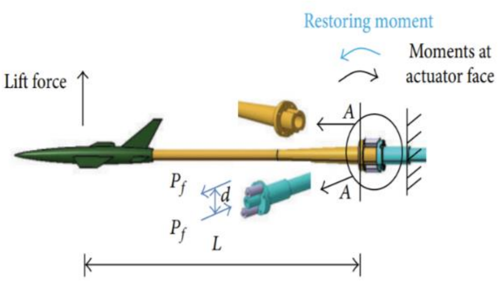


Figure 3 Sting-damping actuator design concept piezoelectric [10-17]

In Figure 4, the conceptual design of a sting-damping actuator includes the use of piezoelectric crystal devices that function as substantial capacitors. It has the unique property of expanding in size in direct proportion to the electric charge that is applied to them. In other words, the piezoelectric crystals within the actuator can change their physical dimensions when subjected to an electrical charge, and this expansion is directly proportional to the magnitude of the charge they receive. This characteristic allows for precise control and manipulation of the actuator's movements, making it a valuable component in various applications that require fine-tuned adjustments and responses. When this expansion is constrained mechanically, it generates a resultant force on the restraint. With a force bandwidth of 30 KHz, piezoelectric actuators can swiftly convert voltage into force, enabling nearly instantaneous force generation. This force-generating capability is utilized for the damper. Upon electrical activation, the vertical actuators can generate a pitching moment at section A-A of the sting. This moment, which forms around the sting's neutral bending axis, is determined by the force (Pf) exerted by the actuators and the distance "d" between their centers.

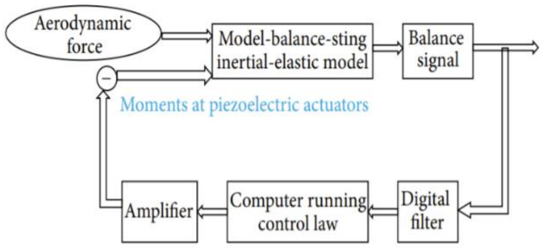


Figure 4 The lift force generates a bending moment

In figure 5, the lift force-induced bending moment at the actuator cross-section can be countered by an equivalent restoring moment of magnitude "$2Pfd$." As a result, the net torque at the sting's cluster face section is eliminated. Figure 5 presents a diagrammatic depiction of the active damping system is presented. This system is capable of reacting to both the aerodynamic forces and the moments generated by piezoelectric devices. The control system for the piezoelectric actuator relies on a balance signal that is used as feedback within the control loop. This signal is first processed by a digital filter to refine its quality before it is fed into the control algorithm, which is run by a computer. Once the control algorithm has been applied, the resulting output signal is then amplified. This amplified signal is subsequently used to actuate the piezoelectric cluster. The activation of the piezoelectric cluster creates a counteracting torque, which serves to counterbalance and reduce vibrations within the sting. In essence, the balance signal, after being filtered and processed, guides the operation of the piezoelectric cluster to effectively dampen any oscillations or vibrations, ensuring a stable and controlled environment within the system.

2.2 Classical PID algorithm

A PID controller is a type of feedback controller that is widely used in control systems to control various processes. It stands for Proportional-Integral-Derivative controller, which means it uses three basic modes of control to regulate the process variable to a set point [3-11].

The explanation of the three terms:

1. Proportional (P): This term is the most basic form of control. It adjusts the controller output based on the current error. The larger the error, the larger the adjustment. The proportional gain ($K_{p)}$ is the parameter that determines the magnitude of the output change in response to the error.

2. Integral (I): The integral term deals with the accumulation of error over time. If the system has a persistent error, the integral term will continue to increase, which helps eliminate steady-state errors [12]. The integral gain (K_i) determines how aggressively the controller will respond to the accumulated error.

3. Derivative (D): The derivative term anticipates future trends and changes. It uses the rate of change of the error to predict future deviations from the set point. This can help dampen oscillations and overshoots. The derivative gain (K_d) controls the sensitivity of the controller to the rate of change of the error.

The general equation for a PID controller is:

$$u(t) = Kpe(t) + Ki \int_0^t e\,(\tau)d\tau + K_d \frac{d}{dt} e(t) \tag{13}$$

Where:

- $u(t)$ is the controller output at time (t).

- e(t) is the error at time (t), which is the difference between the set point and the process variable, K_p is the proportional gain, K_i is the integral gain and K_d is the derivative gain.

The integral term is often implemented as a summation rather than an integral to avoid issues with differentiator noise:

$$u(t) = K_p e(t) + K_i \sum_0^t \mathrm{e}\ (\tau) d\tau + K_d \frac{d}{dt} e(t) \tag{14}$$

This equation can be implemented in different forms, such as parallel, ideal, and series forms, which combine the P, I, and D terms in different ways to form interdependent system responses.

It's important to note that tuning a PID controller involves finding the right balance between the P, I, and D gains to achieve the desired system response. This is often done through trial and error or using systematic tuning techniques [5-13].

In a PID controller, the integral term (Integral, often denoted as I) serves to accumulate past error over time, which is essential for eliminating steady-state errors in control systems [14]. The integral term's output is proportional to both the magnitude and the duration of the error. The mathematical expression for the integral term is:

$$u_I(t) = K_i \int_0^t \mathrm{e}(\tau) d\tau \tag{15}$$

Where:

- $u_I(t)$ is the integral term's contribution to the controller's output at time (t).

- (K_i) is the integral gain, which determines the impact of the integral term on the controller's output.

- $\mathrm{e}(\tau)$is the error at time (τ), which is the difference between the set point and the process variable.

- $(\int_0^t)$ represents the integral from the start time of the system to the current time (t).

In practical applications, the integral term is crucial for achieving high precision and stability in control systems, especially in scenarios that require high-precision control. However, the use of the integral term must be approached with caution to avoid issues caused by noise, and the integral gain must be carefully adjusted to ensure the best balance between system stability and responsiveness [15].

2.3 Neural network-based fractional PID (NNPID):

The Neural Network PID (NNPID) Algorithm is a control strategy that combines traditional PID control with neural networks. It uses neural networks to learn and adapt to system dynamics, improving control performance in complex and nonlinear systems. The algorithm takes input signals, applies PID principles, and adjusts control outputs based on learned patterns, continuously adapting to changing conditions for optimal control [16].

$$I_{out} = \frac{1}{T_i} \int edt = K_I \int edt \tag{16}$$

In this context, I_{out} denotes the integral part of the controller's output, T_i signifies the reset time or integral time and K_i stands for the integral gain [17-18].

The derivative term (D) primarily aims to dampen the system's oscillatory response. Unlike the integral term, it does not address offset or alter the system's nature and order. Instead, it focuses on analyzing the rate of change of the error signal. The derivative term's influence is particularly evident in larger system responses to rapid changes. However, it requires careful adjustment over time. Excessive derivative term can result in unstable control or overshoot, highlighting the importance of balancing its contribution to the overall control scheme [4-19].as shown in equation (18):

$$D_{out} = T_d \frac{de}{dt} = K_D \frac{de}{dt} \tag{17}$$

In this context, D_{out} symbolizes the derivative component output controller, T_d signifies the derivative (t) time, and K_D denotes the derivative gain as shown in figure 6.

3. Methodology and Implementation

The performance of both the classical PID and BP NN control algorithms was initially assessed in a laboratory setting using an aluminum cantilever beam instead of the sting typically found in wind tunnels. The experiment setup involved a diagram depicting the configuration and a photograph showing the cantilever beam subjected to stimulation by a fan, mounted on a fixed base, a pair of PZT5H piezoelectric plates were affixed to opposite surfaces of the beam near its end. The upper piezoelectric plate served as a sensor to monitor the amplitude of the beam's vibration, as the voltage generated by this plate was directly proportional to the beam's deformation or strain at the plate’s location. The modeling aims to recreate the distributed structure details of the tail strut while balancing the computational load to achieve more precise modes. The bottom surface of the base is designated as a fixed surface, allowing for the calculation of the tail strut structure modes. This process yields the first and second-order pitch and yaw modes along with their corresponding vibration shapes as seen in table 1.

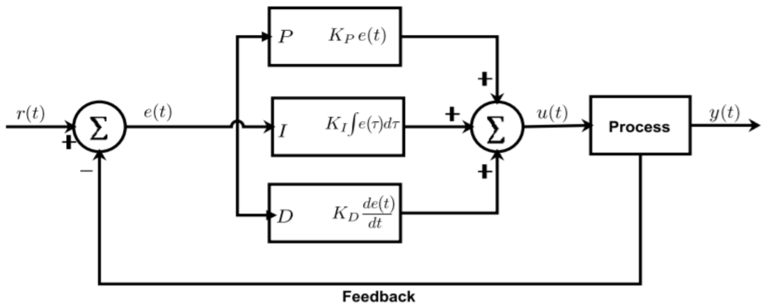


Figure 5 PID BPNN control block diagram, standard configuration of a PID control system [20]

Table 1 Parameters of Tailstock Structure

Parameters	Value	
makings	F141	PIC151
Modulus of elasticity [GPa]	183.5	100
Poisson's ratio	0.27	0.34
Density [$g\ /\ cm^3$]	8	7.8

This deformation was linearly amplified, resulting in a substantial displacement observed at the beam's tip. The signal from the plate was then acquired by a data acquisition card installed in the computer, serving as input for the control law. The opposite plate was used as an actuator connected to the amplifier which magnified the output of the control algorithm, the properties of the fan in table 2 and PZT5H plates at table 3.

Table 2 Fan properties

Parameters	Value
Rated power	50 W
Air quantity	1.03 m3 /s
Maximum wind velocity	3.07 m/s

Table 3 PZT5H properties

Parameters	Value
K_{31}	0.41
K_{15}	0.68
$D_{31}(10^{-12}C/N)$	550
$S_{11}^{E}(10^{-12}m^2/N)$	16.7
$S_{33}^{E}(10^{-12}m^2/N)$	21.5
$\rho(kg/m^3)$	7600

4. Results and Discussion

Figure 7 illustrates the Curves generated from the operation of a BP neural network control system can be observed in the output, showcasing clear distinctions. The designed BP The neural network control system has shown remarkable stability and has proven effective in reducing instability within the system that may be caused by delays. Additionally, it is capable of swiftly following the system's response patterns. The control system, which is based on neural networks, exhibits excellent stability, it is successful in mitigating instability within the system that could arise from delays, the system is able to promptly track and respond to changes within the system. This aims to maintain the original meaning while presenting it in a more structured and detailed manner, thereby enhancing control system performance.

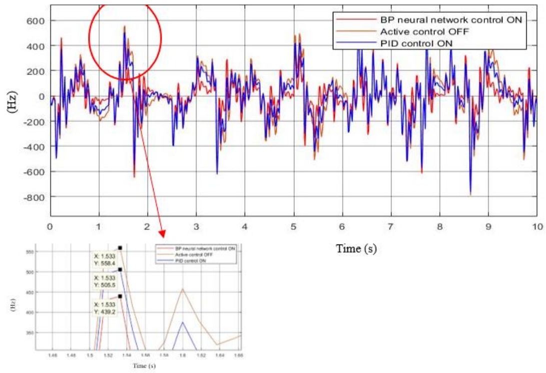


Figure 6 Vibration supresstione efficiency control results

Moreover, with BP neural network control in action, the system's dynamic response adjustment time is significantly reduced. This improvement stems from the deep learning algorithm's capability to adjust PID parameters in real-time during the system's dynamic response, enabling timely adjustments in response to system errors.

Consequently, the control system exhibits accelerated response rates, leading to notable enhancements in overall system adjustment time.

In summary, the BP neural network control system adeptly tracks system responses, efficiently suppresses interference-induced instability, and bolsters control system performance.

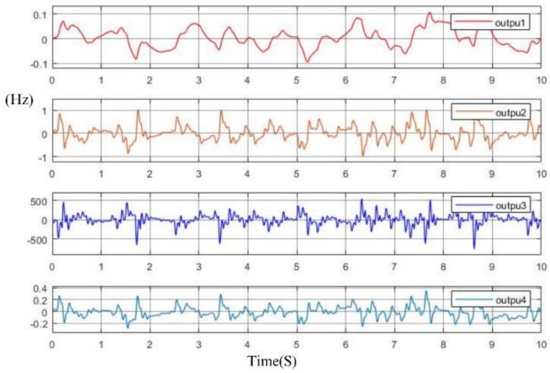
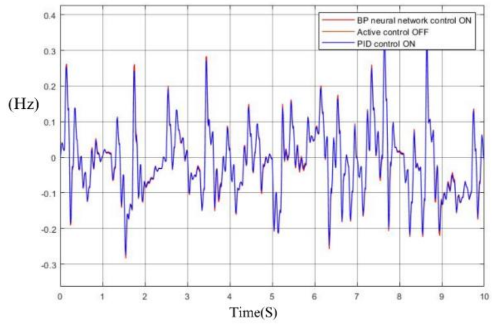
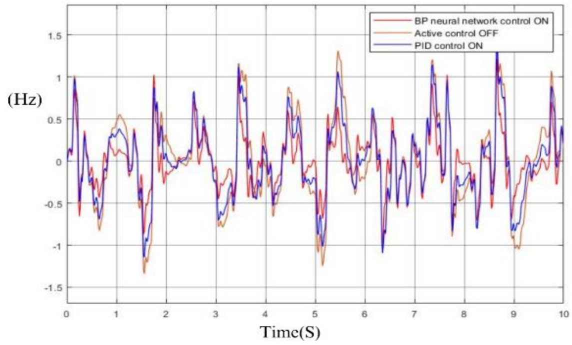


Figure 7. Output curve under BP neural

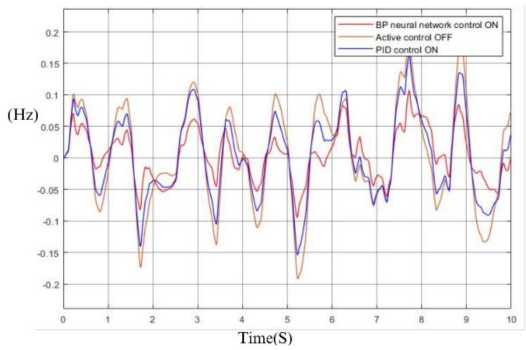
At figure 8 depicts a comparison of the output from various controller systems. It is evident that the BP-NN PID control strategy outperforms both the PID controller and passive suspension across all metrics.



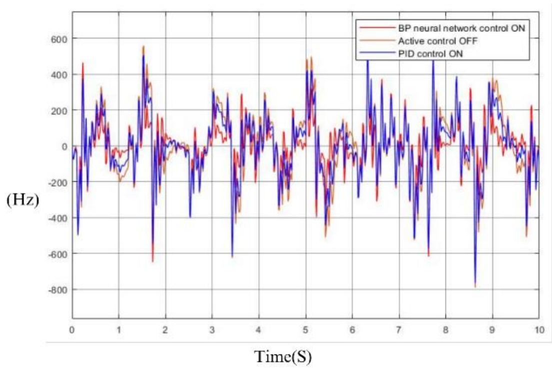
(a) Model airflow responds first test



(b) Model airflow responds second test



(c) Model airflow responds third test



(d) Model airflow responds fourth test

Figure 8 (a,b,c,d) is models response to unstable airflow with active control ON/OFF in wind

On the other hand, (NNPID) the Non-linear Neural PID Algorithm integrates (BP-NN) back-propagated networks and implements a self-learning and evaluation PID control approach utilizing the BP neural network as shown at figure 9. This technique utilizes a model based on a linear neuron that is capable of adapting. It also makes use of a learning process known as supervised error correction, which is facilitated by an optimization method called gradient descent, specifically employing the Delta rule to adjust the model's parameters. The NNPID Algorithm operates within a neural network framework, providing it with the flexibility and learning abilities needed to effectively handle the nonlinear characteristics and uncertainties present in intricate dynamic systems. This makes it a strong solution for such scenarios. Nonetheless, the algorithm's complexity and the computational resources it requires can present difficulties when attempting to apply it in real-time settings. The NNPID Algorithm functions within the context of a neural network, which equips it with adaptability and learning capabilities, these features enable it to robustly address the nonlinearities and uncertainties inherent in complex dynamic systems, the sophistication of the algorithm and its high computational demands can create challenges for its use in real-time applications.

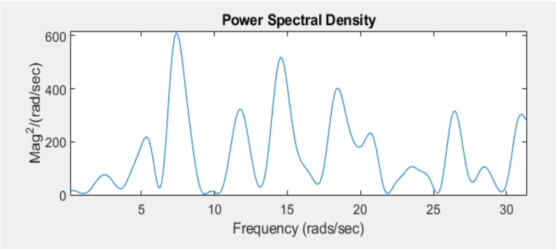
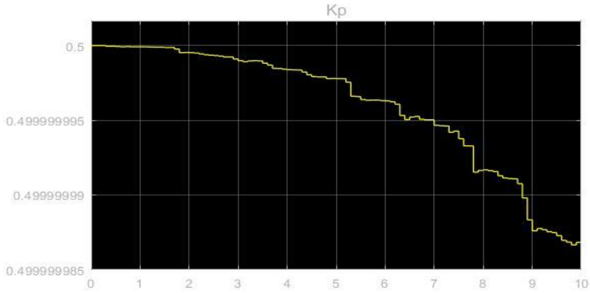


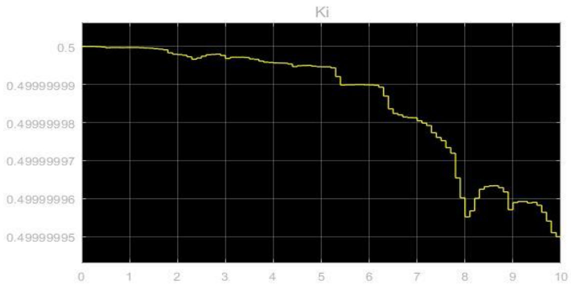
Figure 9 PSD for BB neural network PID

Figure 10. provides valuable insights into the performance and effectiveness of the BP neural network control system. This system demonstrates several key advantages, including stability enhancement, suppression of system instability caused by delay, quick response to system changes, and overall improvement in control system performance.

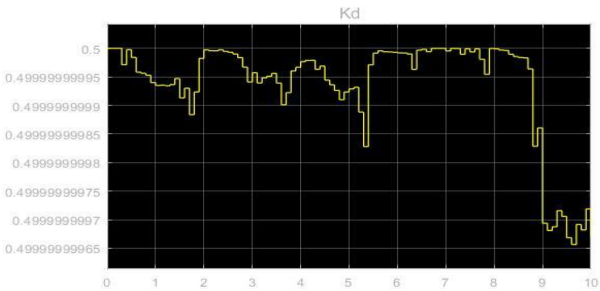
5. Conclusion



(a) K_p



(b) K_i



(c) $\boldsymbol{K_d}$

Figure 10 (a) $\boldsymbol{K_p}$ (b) $\boldsymbol{K_i}$ and (c) $\boldsymbol{K_d}$ values of BB neural network PID

From Figure 11. We can see (a) K_p is in decreasing way which means Stability Improvement on the positive side, decreasing K_p can improve stability in the Sting Active vibration in wind tunnel lab, because the system is need to be prone to oscillations or if there are significant disturbances that need damping.

Also, from figure 11. (b) K_i Increased Stability by decreasing Damping values K_i from 0.5 to less than 0.49999995, lower Ki values dampen the integral contribution, which can help in stabilizing the system.

And from figure 11. (c) K_d is processing the errors corrections K_d by seeing Oscillations changes from 0.5 to 0.4999999995 then increasing again until last value at 0.499999997 that's means Reduced Damping, for damping rapid changes in the error signal. When K_d decreases, the damping effect of the derivative action diminishes. This can lead to a slower response to rapid changes, which means the relationship is $K_d < K_p > K_i$.

In this of a damping system using a BP (Back-Propagation) Neural Network (NN) control, the arrangement ($K_d < K_p > K_i$) refers to the relative influence and functionality of the proportional, derivative, and integral terms in the control algorithm. Which means:

1. Derivative Gain K_d (K_d < K_p):

In a damping system controlled by a BP NN, having K_d smaller than K_p that the control system emphasizes damping rapid changes or fluctuations. The derivative term helps in smoothing out sudden variations or oscillations in the system's output.

2. Proportional Gain K_p (K_p > K_i):

With K_p larger than both K_d and K_i, that means the system gives significant importance to the proportional term. This implies that the control response is primarily proportional to the current error signal. A higher K_p leads to a more aggressive and immediate response to deviations from the desired state.

3. Integral Gain K_i (K_d < K_p):

The integral term K_i is responsible for eliminating long-term steady-state errors by integrating the cumulative error over time. However, with K_i smaller than K_p, the system may not focus as much on correcting prolonged error accumulation as it does on immediate error response.

The main results of this research, in the method of a BP NN control system for damping, the configuration ($K_d < K_p > K_i$) suggests a prioritization of addressing rapid changes and immediate errors over long-term error accumulation. This configuration can be effective in systems where quick responses to dynamic changes are crucial, while still ensuring stability and control over the system's behavior.

The NNPID algorithm has giving positive reflections potential and significantly enhance the wind tunnel examine experimental lap by providing independent and robust control. Importantly, this mechanism eliminates the need for dependence on balance signals. The novel system for vibration mitigation is designed to be highly effective by incorporating a comprehensive strategy. This involves the creation and incorporation of stackable piezoelectric actuators, which are used to counteract vibrations. Additionally, the system leverages feedback on the velocity of the aircraft model to further enhance its performance. The new system adopts a holistic approach to vibration mitigation, it includes the design and integration of piezoelectric actuators that can be stacked for enhanced effect, the system also utilizes feedback from the velocity of the aircraft model to optimize its performance, these features collectively position the system for optimal vibration reduction. The rephrased version aims to convey the same information but with a slightly different structure and emphasis for clarity and variety. We can see the gap result between BP NNPID, classic PID and active control off it shows in figure 7. It maintains the accurate results with more stable vibration control system.

By conducting side-by-side evaluations with other recognized methods, the effectiveness of the NNPID algorithm was confirmed. Additionally, these comparisons shed light on the algorithm's comparative advantages and limitations across various practical situations. The BP NN-PID algorithm's strength and flexibility were highlighted by thorough testing, as well as demonstrated through its ability to effectively tackle fundamental vibrations within the pitch plane. This capability is crucial for maintaining the accuracy and reliability of the testing procedures.

In another way:

a) The BP NN-PID algorithm was subjected to extensive testing to underscore its robustness and adaptability.

b) A key highlight was its effectiveness in managing primary vibrations specifically in the pitch plane.

c) This feature is significant as it ensures the integrity of the testing process by addressing potential disturbances.

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