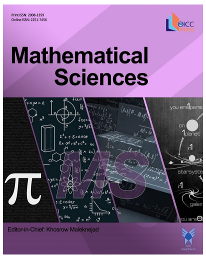

Math. Sci. 2025; 19(2): 1-9

Mathematical Sciences (MS)

https://doi.org/10.57647/mathsci.2025.1902.06

A Mathematical Approach to Intelligent Control in Artificial Heart Pacemaker Design Using ANFIS with FCM, GA, and PSO

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Original Research

Received:
17 April 2025

Revised:
29 May 2025

Accepted:
16 June 2025

Published online:
30 June 2025

Abstract:

This paper presents the design and comparison of an Adaptive Neuro-fuzzy Inference System (ANFIS) based controller of a pacemaker with Fuzzy c-means clustering, Genetic algorithm, and Particle swarm optimization learning methods. At the same time, ANFIS is using the benefits of fuzzy logic and neural networks. The input-output data for the FCM, GA and PSO-based ANFIS heart rate controllers shall be developed after the design of a (proportional integral derivative) PID-based heart rate controller so that they can be trained and tested.

The results of the Step response in Time domain, have been compared with previous studies and show an optimal pacing rate achieved by ANFIS_GA which is used to automatically set a heart rate for each patient more accurately than other methods, such as Fuzzy, PID and FPID.

FCM and PSO have their strengths and can perform well in specific scenarios, but GA tends to outperform them due to superior exploration capabilities, robustness across problem types, and effective handling of multi-objective optimization. The combination of genetic diversity, population-based search, and adaptability makes GAs a powerful choice for complex optimization tasks, particularly when convergence properties are critical. Compared to other training methods, the convergence rate was better for FCM. GA's accuracy was superior to all the other methods.

A MATLAB script is used for the controller design. The resulting 'FIS' (fuzzy inference system) file is imported to SIMULINK and simulation is done by fuzzy controller block that uses ANFIS 'FIS' file.

GA based ANFIS simulation results for determining Membership function's coefficients show better results than other methods. There is no overshoot and settling time is about 3.13 seconds and rise time 2.28 seconds for step input response (85 bpm input). Beyond this application, this work demonstrates a novel integration of clustering and metaheuristic methods for stability-constrained adaptive fuzzy control, contributing to the theory of nonlinear optimization and function approximation applications in control systems.

Keywords: Adaptive Neuro-Fuzzy Inference System (ANFIS); PID; Fuzzy C-Means Clustering (FCM); Genetic Algorithm (GA); Particle Swarm Optimization (PSO); Heart rate; Pacemaker

Cite this article: Dabiri Aghdam A., Jafarnia Dabanloo N., Nowshiravan Rahatabad F., Maghooli K. A Mathematical Approach to Intelligent Control in Artificial Heart Pacemaker Design Using ANFIS with FCM, GA, and PSO. Math. Sci 2025; *19*(2): 1-9 https://doi.org/10.57647/mathsci.2025.1902.06

1. Introduction

ANFIS[1] is a method for approximation of functions and control of biomedical and other signal processing problems, using fuzzy algorithms. A pacemaker is a device that generates electrical pulses and delivers them to the heart by electrodes which are placed on the muscles of the heart. The first several seconds of control time for controller designs should be considered to arrive at a fast response.

In the area of computational optimization, searching for efficient algorithms has led to significant mathematical achievements that enhance performance and usability of numerous approaches [2].

- Genetic Algorithms (GA) represent a powerful paradigm with their characteristic optimization processes, i.e., selection, crossover, and mutation operators mathematically proven to maintain genetic diversity as well as facilitate global search capabilities[3]).This paper examines the mathematical foundations of GAs focusing on their convergence properties and stability analysis, which provide insight into their capacity to explore and search complex solution spaces. Alternative optimization methods alongside different areas of evolutionary computation, including neural networks. Each of the most fit chromosomes that the genetic algorithm discovers are then utilized as an initial point for the hill-climbing algorithm, which adheres to the gradient of the evaluation function from there to a local maximum, [4].

- Fuzzy C-Means (FCM) relies on mathematical models which approximate within-cluster variance minimization by iterative optimization of cluster centers. Its initialization sensitivity and local optimization bias limits its robustness to a broad range of problem types. Mathematical frameworks that underlie FCM recognize the need for developing new techniques with which these limitations can be overcome.

- Particle Swarm Optimization (PSO) uses a mathematical model based on swarm intelligence, where particles adjust their positions according to personal and global bests. While PSO has the capability of rapid convergence, its lack of diversity maintenance mechanisms may cause instability in high-dimensional space. The paper discusses the mathematics of these dynamics and provides potential improvements through hybridization with GA approaches. By critically analyzing the mathematical innovations underlying such optimization methodologies, e.g., advanced stability analysis, adaptive parameter tuning, and multi-objective optimization paradigms, this study aims to clarify the situations in which GAs outperform FCM and PSO. The findings underline the importance of mathematical accuracy in designing optimization algorithms with which to challenge complicated issues across domains.

This paper presents design, analysis and comparison of an ANFIS pacemaker controller with FCM, GA and PSO methods for optimizing the coefficients of membership functions (MF) of premise and consequent parameters with non-fuzzy regular PID methods. The design is based on PID and FPID to regulate heart rate, according to most of the prior work. To detect the heart rate and patient activity, they used two sensors with these methods to adjust heartbeats.

In [5], the design was based on ANFIS with Gradient Descent and Grid Partitioning, but we have used FCM, GA and PSO and a comparison among them are done. GA has demonstrated better results in offline simulation and increasing the speed of regulation of the heart rate in the time domain step input response in the generation of fuzzy 'FIS'.

This research not only contributes to ANFIS theoretical understanding but also proves its practical feasibility to tackle key biomedical problems. By bridging innovative mathematical techniques and their medical applications, we pave the way for future research that can further enhance patient care using new computational techniques.(the overshoot is a very important parameter that affects patient heart rate regulation, higher heart rates(more than 150 bpm) that is called atrial fibrillation(AF) may cause death of patients that using artificial pacemakers.

Function approximation is essential in numerous domains, including economics, engineering, and computing, and is applied in areas like pattern recognition, data mining, system identification and control. The main objective of any function approximation method is to establish a suitable relationship between input variables and their corresponding outputs, even when working with a limited dataset. There are various techniques for function approximation, ranging from traditional analytical methods—such as least squares linear regression, polynomial fitting, and shape-preserving techniques—to more advanced intelligent methods, including those utilizing fuzzy logic, neural networks (NNs), or hybrid neural-fuzzy systems. Both neural networks and fuzzy logic are effective as universal approximators, provided they include a sufficient number of hidden neurons in NNs or enough rules in fuzzy systems to achieve robust results in nonlinear function approximation. This study uses ANFIS models to estimate functions(Input and output data of PID step response of system), assessing their performance by comparing them using the root mean square error (RMSE) metric. [6]

2. Baseline control architectures (PID and fuzzy-PID)

Regular control and fuzzy PID control methods have been introduced by Wei Vivien SHI and et al [7, 8, 9, 10]. The main goal was to design a fuzzy-based controller for an artificial pacemaker, that is difficult to model them because of existing mathematical modelling methods and model nonlinearities[11, 3]. Figure 1 shows their proposed block diagram.

3. ANFIS Controller

MATLAB PID autotune toolbox is used to tune PID parameters for optimum rise time, overshoot, settling time (Figure 2).

3.1 ANFIS Controller Design

Artificial Neural Networks (ANNs) can make numbers all day—super good at learning patterns. Fuzzy logic, on the other hand, is full of intuition and expert know-

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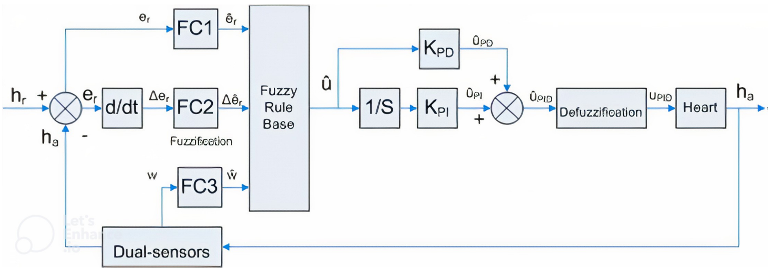

Figure 1. Wei Vivien SHI and et al proposed block diagram

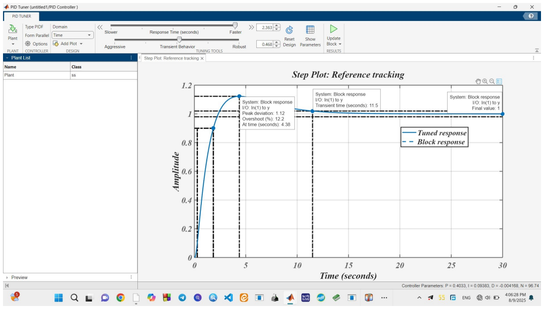

Figure 2. MATLAB PID autotune toolbox— showing rise time, overshoot, settling time

how, not just raw calculation. ANNs handle the number-crunching, learning those fuzzy membership values, building IF-THEN rules, and sorting out logic. Fuzzy logic provides a systematic framework, facilitates coherent interpretation of complex phenomena and allowing the incorporation of expert knowledge and experiential insights.

This combination is called a hybrid neural/fuzzy system [12].

The ANFIS is tuned automatically by the least-square-estimation and the back-propagation algorithm.

3.2 ANFIS optimization methods

The ANFIS model (see Figure 3 for with single I/O model) is basically a modified version of a Takagi-Sugeno Fuzzy Logic Controller (TS-FLC). Imagine it as a five-layer system:

- L1: Inputs go here
- L2: Membership functions for those inputs (how much does this input belong to a certain group?)
- L3: Fuzzy rules (the classic IF this, THEN that)
- L4: Output membership functions
- L5: Output values (what you get out)

Everything except the neural net block is just standard fuzzy inference system (FIS) stuff. But the magic is, ANFIS uses least squares estimation and backpropagation to keep getting better[13].

3.3 Designing an ANFIS controller for an artificial Pacemaker

The ANFIS controller will convert the output signal into a reference heart rate and compare it to that. Compared to other fuzzy and fuzzy PID control methods, the ANFIS demonstrated better control results for the generation of pacing pulses including rate and amplitude of heart rate signals.

3.4 ANFIS learning methods

The method of data collecting through the Internet will not be feasible, given that learning data are collected using ECG parameters in patients. Instead, the ANFIS controller parameters will be trained based on offline data from healthy people with similar parameters of the patient's age, sex, resting and walking, etc., or the same patient in normal situations and at earlier stages of the disease.

Method of learning through offline training is as follows:
1.Grid Partitioning (GP): 2. Subtractive clustering (SC): 3. Fuzzy C Means (FCM): 4. GA 5. PSO
in [5] work, methods 1 and 2 have been examined. The methods used and compared to other methods in the present study are FCM, GA or PSO. The speed of FCM learning convergence is much faster than the GP and SC method.

3.5 Design of ANFIS controllers based on FCM, GA, PSO methods and comparison with other Grid Partitioning -Subtractive clustering learning methods

We developed codes to achieve these results, since FCM and GA and PSO methods are not available in MATLAB tools. For training data, 75% of the data are used, and 25% for testing data. For FCM, GA and PSO, the following parameters shall apply:

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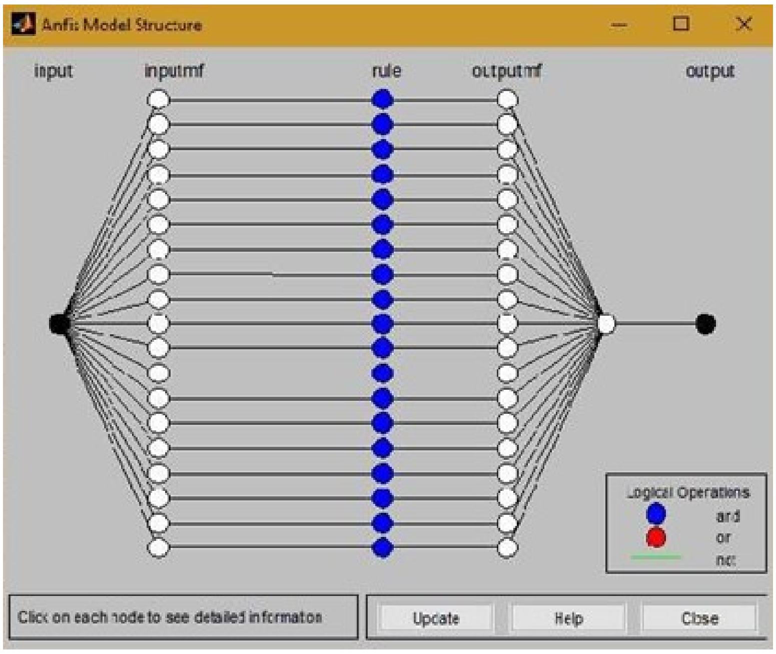

Figure 3. ANFIS model with single I/O showing the ANN architecture

```
-------------------- PSO (Particle swarm optimization) Parameters
       alpha=1;
 Params.MaxIt=500;          \% Maximum Number of Iterations
 Params.nPop=100;
 MaxIt=Params.MaxIt;      \% Maximum Number of Iterations
 nPop=Params.nPop;        \% Population Size (Swarm Size)
 w=1;                     \% Inertia Weight
 wdamp=0.99;                   \% Inertia Weight Damping Ratio
 c1=1;                   \% Personal Learning Coefficient
 c2=2;                                 \% Global Learning Coefficient
-------------------- GA (Genetic Algorithm) Parameters --------------------
 Params.MaxIt=500;
 Params.nPop=100;
 MaxIt=Params.MaxIt;
 nPop=Params.nPop;            \% Population Size
 pc=0.7;                                 \% Crossover Percentage
 nc=2*round(pc*nPop/2);     \% Number of Offsprings (Parents)
 pm=0.5;                               \% Mutation Percentage
 nm=round(pm*nPop);         \% Number of Mutants
 gamma=0.2;
 mu=0.1;           \% Mutation Rate
 beta=8;            \% Selection Pressure
-------------------- FCM (fuzzy c-means clustering) Parameters --------------------
 Number of Clusters =10
 Partition Matrix Exponent = 2
 Maximum Number of Iterations =100
 Minimum Improvement = 1e-5
 Params.MaxIt=10;
 train\_Epoch=100;
 train\_ErrorGoal=0;
 train\_InitialStepSize=0.01;
 train\_StepSizeDecrease=0.9;
 train\_StepSizeIncrease=1.1;
 OptMethod.Hybrid=1;
 OptMethod.Backpropagation=0;
```

Figure 4 and Figure 5 show the sample output of the MATLAB simulation , showing input and output data and and errors for Grid Partitioning and Subtractive clustering methods. At this paper function approximation property of ANFIS is used to approximate output response of controller based on input given data.

The minimum root means square error (RMSE) for ANFIS membership functions parameter optimizations for all data including train and test are:

- Grid Partitioning Subtractive clustering: RMSE = 2.7251
- Fuzzy C Means (FCM): RMSE = 3.13
- Genetic Algorithm (GA): RMSE = 4.8
- Particle swarm optimization PSO: RMSE = 5.17

Output step response's rms errors (RMSE) that are different between ideal step input and real output are:

- ANFIS FCM: RMSE= 14.1574
- ANFIS GA: RMSE= 14.1177
- ANFIS PSO: RMSE= 14.0362

4. Heart Models and Simulations at SIMULINK environment

There are a lot of heart models introduced including mathematical [14, 15], electrical (Vanderpol and modified Vanderpol equations)[16, 17] [18], YNI mathematical-physiological model , IPFM [19] [14] and Vanderpol Oscillators. In this paper, we chose the Laplace transfer function model [20]. The time-domain block diagram and Simulink simulation model of the new ANFIS controller are shown in Figure 6 and Figure 7.

The training data are stored in the PID upper part of the controller. The MATLAB PID (Figure 7) object has been used to optimize the heart model's time domain response, so that input and output of PID block signals have been imported into a MATLAB workspace. Then the stored IN/OUT data is entered as the training data to the MATLAB ANFIS toolbox. For training data, the GUI Load Data command is used to generate the 'FIS' file with grid partitioning or hybrid backpropagation and recursive least squares as optimization methods. The heart transfer function and pacemaker models, as described at [20] used at simulations and is shown in the equations below:

The system Laplace transfer function model.

$$8/(s \ +8) \tag{1}$$

and model of heart is given by following transfer function:

$$169/(s2+20.8) \tag{2}$$

The ANFIS controller's base and subsequent parameters have been trained using the Back Propagation method. The parameters are adjusted by FCM, GA and PSO methods in the present work. GA's results are more favorable, as has been shown in previous paragraphs.

The lower section of Figure 6 shows the ANFIS controller with Fuzzy Logic box with fis file generated from training phase of ANFIS toolbox and optimized by FCM, GA and PSO algorithms separately. The time domain step response is shown in Figure 7.

The results are shown in Table 1 and Table 2 when the model simulation is performed with step input 85 bpm, PID and ANFIS controller outputs as well as a comparison of them.

It is thought that ANFIS PSO will have some loss in response and should be reimbursed by an increased gain of capital blocks. The GA method responds much more quickly, and all of them don't overshoot. In addition, there are certain additional gains in GA and FCM that should be reduced by a reduction of the gain. There's an 8 % overshoot on the PID controller.

5. Results and Discussion

5.1 Results of comparison of regular PID and fuzzy controller time-domain step input response

Jyoti et al. compared three Ziegler Nichols, Tyreus Luyben, PID tuning and relay methods to a fuzzy controller PID controller. They have shown that the fuzzy controller has a maximum overshoot that is less than that of all the controllers and that it has a better time to rise and settle than other control methods, [21]. Srivastava et al. have implemented our proposed ANFIS controller method in FPGA hardware.[22]

At Table 1, the results of regular PID with our new optimization methods are compared and it is seen that ANFIS based on PSO-GA-FCM has much better rise and settling times than regular PID and has no overshoot. In comparison with current work, Table 2 provides step response parameters from prior work.

5.2 PID and fuzzy controller stability analysis simulation results (Time and Frequency domain stability analysis)

5.2.1 Time domain

All the time-domain design and analysis happened in Simulink (Figure 8). First, you make your training data with the PID controller, then use that to tune up the FIS file (either command line or ANFIS GUI). Grid partitioning and hybrid backpropagation do the job, with recursive least squares fine-tuning the membership functions. The heart and pacemaker models come from Jyoti Yadav et al [21].

FIS file saved after an acceptable rms error (0.38). The simulation result of unity step input response (Rise-time, settling-time, over-shoot) is shown in Table 3.

The over-shoot was less than 2 percent and a rise-time of 2 seconds with settling-time of less than 2 seconds. The parameters have been shown for 60 and 72 and 85

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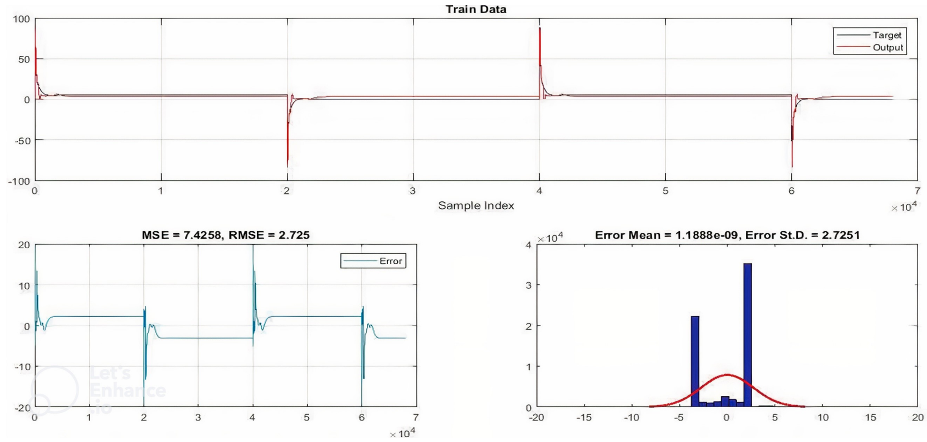

Figure 4. Train Data output for Grid Partitioning and Subtractive clustering methods

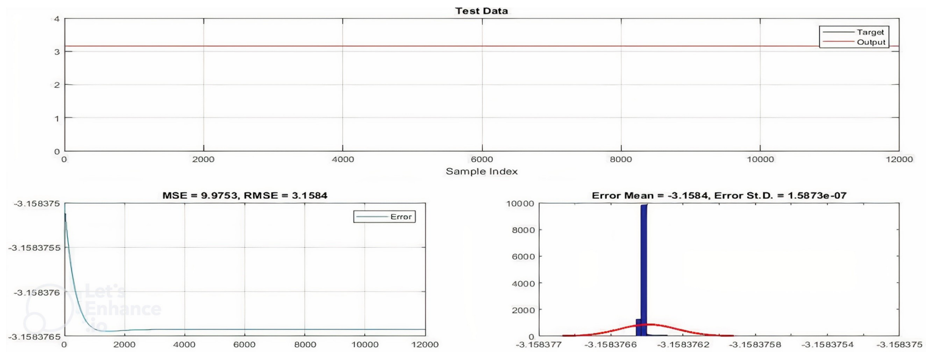

Figure 5. Test Data output for Grid Partitioning and Subtractive clustering methods

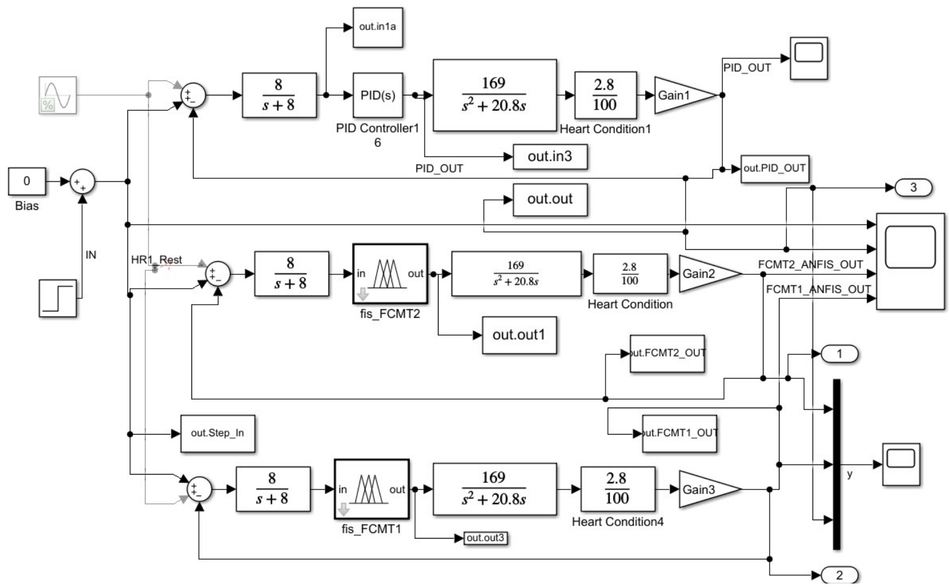

Figure 6. The ANFIS and regular PID controller simulation using the Simulink with the above-mentioned heart and pacemaker models

Table 1. Comparison of time response parameters of the ANFIS controller with GA-PSO-GA Optimization with PID method

Methods	Rise-Time (s)	Max. Overshoot (%)	Settling-time(s)
PID	2.8560	8.1522	17.006
ANFIS_PSO	2.7023	N/A	4.358
ANFIS_GA	2.2882	N/A	3.132
ANFIS_FCM	2.6193	N/A	3.083

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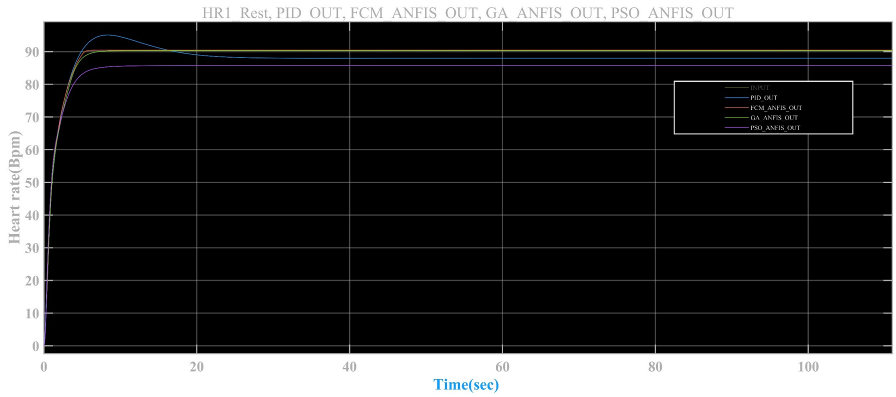

Figure 7. Comparison of output of Step response of regular PID and proposed ANFIS

Table 2. Comparison of current work's parameters with previous works

Type	RMSE	Max-Err.(%)	Max. Oversht (%)	Rise tim.(s)	Sett. time(s)
FPID (SHI, W. V.(2013))	0.889	1.72	N/A	N/A	N/A
Fuzzy (Shi, W. V. (2012))	2.38	4.88	N/A	N/A	N/A
ANFIS_GA (this work)	0.8	1.4	0	2.28	3.13
PID (this work)	0.16	2.03	8.15	2.8	17

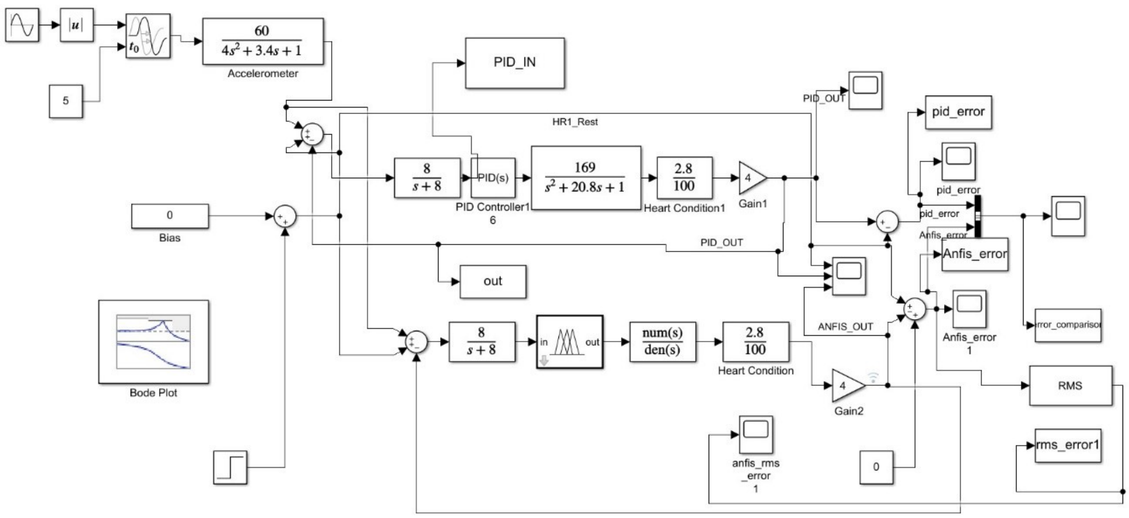

Figure 8. Time domain simulation of PID and ANFIS controllers in Simulink

Table 3. Response parameters of ANFIS controller with various heart rates

HR (bpm)	Rise Time(s)	Settling Time(s)	Max Overshoot (%)
60	1.63	1.23	0.5
72	1.97	1.23	1.53
85	1.7	1.55	1.08

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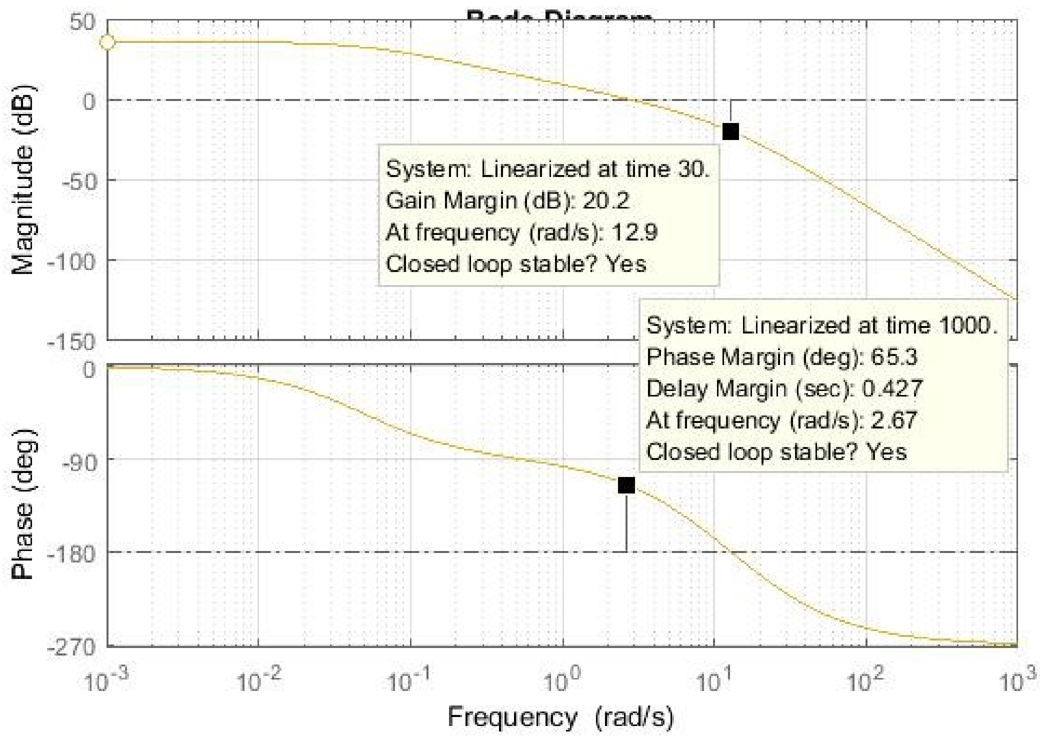

Figure 9. Bode stability check

bpm inputs are shown at Table 3:

Those are the actual results for the ANFIS controller at different heart rates.

5.2.2 Frequency domain

Now, for the stability analysis. we ran the frequency domain analysis using the Bode diagram (Figure 9). The Bode plot shows a gain margin of 42.1 dB and a phase margin of 100 degrees. It is shown that the system is stable.

6. Conclusion

The selection of bode diagrams and step response methods have gotten, due to the nonlinear nature of ANFIS, various stability analysis methods including time and frequency are tested. As a reliable indicator of heart disease, heart rate signals are used. Pacemaker operation depends on the sensors (rate and activity of patient) and the device electronic circuits and on the performance of the heart rate controller that uses various algorithms of speed or rate control systems (in this paper the neuro fuzzy methods are used). Different control methods have been analyzed for the design of a heart rate controller during this research. Initially, to meet the various performance parameters, the MATLAB PID controller was tuned with the help of the MATLAB, PID Tuning GUI tool. An intelligent ANFIS controller with an ANFIS toolbox, developed to enhance the system's performance (Rise time and overshoot). It is observed from the output response of the fuzzy controller that performance parameters (Maximum overshoot, RMSE, and Maximum error) of the ANFIS controller with GA learning algorithm are better compared to the PID and other control methods.

Authors contributions
All the authors have participated sufficiently in the intellectual content, conception and design of this work or the analysis and interpretation of the data as well as the writing of the manuscript.
Availability of data and materials
The data of this study is available from corresponding author upon request by email.
Conflict of interests
The authors declare that they have no known conflict of interests to influence the work reported in this paper.

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