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Design and Optimization of Dual-Chamber Pacemakers Using Hunting Harris-Manta Optimization Algorithm (HMOA) for Enhanced PIDA Control

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Abstract
The design and implementation of a dual-chamber pacemaker system, leveraging the Hunting Harris-Manta Optimization Algorithm (HHMOA) to improve proportional-Integral-Deriavitive-Acceleration (PIDA) control. Dual-chamber pacemakers are critical for regulating atrial and ventricular synchronization, necessitating precise and adaptive control mechanisms. The proposed HHMOA synergistically combines the strengths of Manta Ray Foraging Optimization (MRFO) and Harris Hawks Optimization (HHO) to create a robust hybrid algorithm that fine-tunes the PIDA controller parameters for optimal performance. The HHMOA optimizes key performance metrics, including steady-state error, settling time,energy consumption,rise time, andpeak overshoot. Using MATLAB/Simulink as the simulation platform, the pacemaker system is modelled and the controller's performance under various physiological conditions is evaluated. The hybrid algorithm facilitates a significant reduction in heart rate regulation errors, enhances response times, improves stability, and lowers power consumption, which extends the pacemaker's lifespan and ensures reliable heart rhythm control. Through extensive simulations, the HHMOA demonstrates superior performance over conventional optimization methods, showcasing significant improvements in error minimization, response speed, and energy efficiency. This research highlights the potential of hybrid optimization algorithms in advancing medical device control systems, particularly in the precise and reliable operation of dual-chamber pacemakers.

Keywords: Dual-Chamber Pacemaker, Proportional-Integral-Derivative-Acceleration (PIDA) Control, Hunting Harris-Manta Optimization Algorithm (HHMOA), Hybrid Optimization, MATLAB/Simulink, Performance Metrics, Heart Rate Regulation.

1. Introduction

Over the past few decades, cardiac pacing technology has undergone tremendous evolution for medical professionals to develop more advanced methods to cure arrhythmias and other heart-related conditions (Singhal and Kumar, 2023). Dual chamber pacemakers are receiving a great deal of attention because that they can able to mimic the action of the heart's natural electrical conduction system (Zhang et al., 2022). The atrium and ventricle are stimulated in these devices, resulting in synchronized contractions that closely mimic the actual physiological function of the heart (Albatat et al., 2020). These dual chamber pacemakers are important to maintain the synchronization between the atrial and ventricular contraction and ensuring good function for the cardiac (Biffi et al., 2021). For these patients with heart rhythm disorders, timing is critical to prevent complications, including arrhythmias and heart failure (Garikapati et al., 2022). With its improved capabilities in controlling transient and steady-state responses in such complex systems, the PIDA controller is a promising way to achieve this (MohdTumari et al., 2023). In recent years, PID controller strategies have been used in a variety of engineering fields for accurate control, and employed in dual chamber pacemakers. Integration of additional acceleration feedback into the PIDA control can provide more accurate and responsive control (Ferrari and Visioli, 2022).

The primary intention of this research is to design and optimize a dual-chamber pacemaker system by employing the Hunting Harris-Manta Optimization Algorithm (HHMOA) to increase the performance of PIDA control for improved heart rhythm regulation and efficiency.
The research's major elements are grouped as follows: Portion 2 provides the literature review. Portion 3 discusses the methods involved. Portion 4 presents the findings, and Portion 5 concludes the investigation.

2. Related works

A mathematical model of human heart rate was used by Mohsin et al., (2021) to propose an ideal Immune-PID strategy for controlling and regulating human cardiac activity. With the help of the BBO algorithm, the settings of the recommended immune PID controller were improved. Furthermore, because of the large data store capacity, low energy consumption, and quick operation, FPGA was used to execute the suggested controller design.
A control device was developed by Srivastava and Kumar, (2022) to enhance the cardiovascular system response's strength,and error during steady-state fluctuations, etc. The main limitation of pacemaker controller design was the settling period. That needed to be a minimal delay time among the pacemaker's stimulus delivery and the necessity for a pulse. The suggested controller was more efficient in terms of "learning" and speed because it combined fuzzy logic with neural networks.
Utilizing machine learning techniques like decision tree, SVM, random forests, and AdaBoost, Umesh Pai et al., (2022) presented a unique CAD tool for the precise identification of pacemaker changes. After extracting texture-based radiomics features using the models, the top ten features were input into the machine learning algorithms and after that, they were classified and chosen based on Relief-F ratings.
A novel unbiased method for evaluating each pacemaker's distinctive features was presented by Augustynek et al., (2022). Regardless of the manufacturer, all types of PCM might be tested in the clinical setting using the suggested cardiac pacemaker testing method. The software might be utilized for both the validation of novel techniques for the artificial stimulation of hearts and educational purposes, illustrating current concepts.
A post procedural hazard forecasting technique for PPMI for patients undergoing TAVR was created by Qi et al., (2023). A hazard attainment structure was developed based on the forecast technique and the multivariate logistic regression technique was utilized for the main analysis to assess predictors. To evaluate factors related to the duration from TAVR to PPMI, a Cox proportional hazard model was employed for secondary analysis. Bootstrapping was used inside to validate the approach, and an independent group was used outside.
To reduce the misclassification of several cardiac diseases, a CNN framework based on DL was introduced by Baghel et al., (2020). The heart sound was recorded for a specific amount of time in that model. From recorded PCG signals, pure cardiac sound was recovered using a Gaussian filter to eliminate noise. A data augmentation approach was used for the dataset to strengthen the resistance to noise. Along with several additional layers, the model has seven convolutional layers.
Using ECG data, Hung et al., (2024) developed a DL technique to forecast upcoming PMI and evaluate the ability to predict cardiovascular events. ECG data from patients at academic medical centers served as the training dataset for the DL technique, while patients from community hospitals and medical centers served as further validation.
An enhanced technique for adjusting the PID controller in accordance with the greatest stability degree requirement was provided by Cojuhari et al., (2020). The optimization process was implemented using the multi-objective GA. The tuning parameters of typical controllers were often determined using analytical formulas that relied on the maximum stable degree value, in accordance with the highest stability degree criterion.

3. Methodology

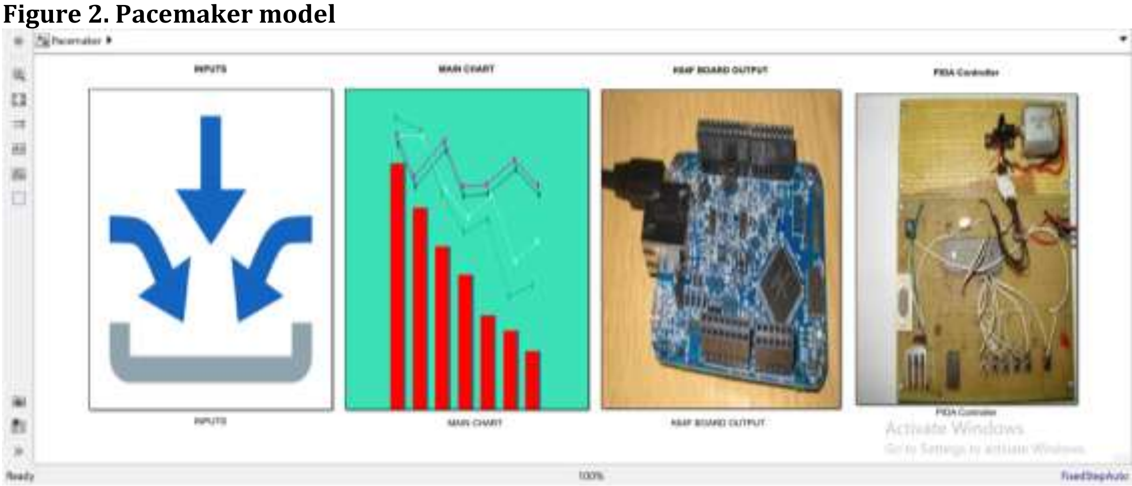
The methodology is summarized as designing the dual chamber pacemaker model in MATLAB/Simulink environment, PIDA-based heart rhythm regulation, and building the hybrid Hunting Harris Manta Optimization Algorithm (HHMOA) to enhance the PIDA controller parameters for optimal performance. The key performance metrics are optimized using this algorithm and simulations are carried out to determine the effectiveness of this algorithm in improving stability, response time, and energy efficiency over conventional methods. The overall flow of the process is exposed in Figure 1.

Figure 1. Overall flow

3.1 Pacemaker model

A comprehensive mathematical model to capture the dynamics of atrial and ventricular pacing is developed in a dual-chamber pacemaker model as shown in Figure 2. This model uses physiological parameters,such as heart rate, conduction delay, and cardiac output,in a more exact manner to represent the cardiac function accurately. Discrepancy equations are used to illustrate the dynamics of the pacemaker, i.e., the relationships between input control signals, such as pacing intervals on theone hand and the output signals corresponding to the resultant heart rhythm on the other. The equations model all of the electrical activity of the heart, including atrial contraction timing, ventricular filling, and the overall synchronization between chambers. This representation of the pacemaker's operational characteristics based on state variables facilitates real-time simulation of its response to changes in physiological conditions. The detailed modeling lays the groundwork for maximizing the pacemaker performance and ensuring the proper heart rhythm regulation in patients with arrhythmias or other heart conditions.

Figure 2. Pacemaker model



3.2 PIDA controller design

Design a PIDA controllerthat extends the traditional PID controller by incorporating acceleration terms. This allows for better handling of dynamic responses in the pacemaker system. Define the controller structure, including proportional (P), integral (I), derivative (D), and acceleration (A) gains.Figure 3 illustrates a block diagram of PIDA that demonstrates the application of the HHMOA to construct an optimum PIDA controller for the cardiac pacemaker. Equation (1) states the transfer functional architecture of the PIDA controller $H_d(t)$, where K_p, K_i, K_d, and K_a represent the proportional, integral, derivative, and accelerated gains, respectively.

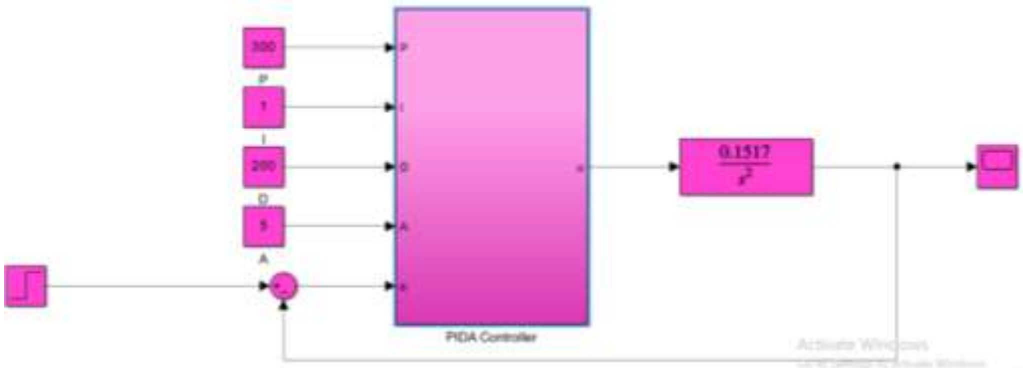
$$H_d(t)|_{\text{PIDA}} = K_p + \frac{K_i}{t} + K_d t + K_a t^2 \quad (1)$$

$$\text{Min } e(.) = \int_0^k \left(f(s)\right)^2 ds = \int_0^s [q(s) - d(s)]^2 ds \quad (2)$$

Equation (2) specifies the objective function $e(.)$, which is the integral of squared error (ISE) among the expected heart rate $q(s)$ and the true heart rate $d(s)$. The restricted functions include the rising time (s_q), steady-state error (f_{tt}), maximum percent overshoot (N_o), and settling time (s_t),which collectively constitute the time-domain reaction specification. To find the proper values of K_p, K_i, K_d, and K_a of the PIDA controller inside their respective bounds (search spaces), as stated in Equation (3), the HHMOA will minimize $e(.)$ and K_a will be set to zero to compare with the PID controller.

$$\text{Subject to} \quad \left.\begin{aligned} s_q &\le 0.5 \text{ sec}, \\ N_o &\le 5\% \\ s_t &\le 1.0 \text{ sec}, \\ f_{tt} &\le 0.01\% \\ 0 \le L_o &\le 5.0, \\ 0 \le L_j &\le 0.1, \\ 0 \le L_c &\le 0.5, \\ 0 \le L_b &\le 0.1 \end{aligned}\right\} \tag{3}$$

Figure 3. PIDA controller block diagram



3.3 Implementation of Hunting Harris-Manta Optimization Algorithm (HHMOA)

Develop the HHMOA by combining the HHO algorithm and the MRFO algorithm. To improve exploration and exploitation capacities, the combined technique makes use of the advantages of both algorithms.A novel approach like the PIDA controller is used to integrate the Hunting Harris Manta Optimization Algorithm (HHMOA) for optimizing control strategy tuning medical devices. HHMOA can be regarded as the combination of adaptive techniques of the HHO and MRFO, thereby improving the exploration and exploitation capability of traditional optimization techniques, and showing clear advantages in complex, dynamic environments. The more responsive and adaptive control mechanism for pacemaker systems is provided by the PIDA controller that incorporates acceleration instead of the classical proportional, integral, and derivative controller. This novel configuration facilitates improved patient-specific tuning of critically needed accuracy in cardiac rhythm management. The optimization of these controller parameters, combined with the creation of a Simulink model of the pacemaker, enables real-time simulation and sensitivity testing of control performance on simulated physiological conditions. This hybrid optimization strategy not only improves the performance of the PIDA controller but also lays the foundation for future developments in the design of medical device control systems, which will maintain patient safety and at the same time optimize the functionality of the system through innovative algorithmic design.

3.3.1 Harris Hawks Optimization (HHO) algorithm

The collaborative foraging habits of Harris Hawks served as the model for the HHO algorithm, a meta-heuristic algorithm. Predatory birds like Harris Hawks effectively carry out cooperative foraging in a number of stages, such as tracking, siege, and attack. Each step is described in detail as follows:

Stage of Exploration

During this stage, Harris Hawks live in large trees or on telephone poles, using their keen vision to wait, search, and find their intended prey's whereabouts. In the HHO method, the previously indicated search behavior is known as the broader exploration phase, and Equation (4) provides a mathematical description of the behavior.

$$w_j^{s+1} = \begin{cases} w_{rand}^s - q_1 * \left|w_{rand}^s - 2 * q_2 * w_j^s\right|, r \ge 0.5 \\ (w_{rabbit} - w_{mean}^s) - q_3 * (ka + q_4 * (ka - va)), \; r < 0.5 \end{cases} \tag{4}$$

Here r is the conversion factor, w_{rabbit} is a single member of the present species at the ideal location (prey), and the outcome is a randomly distributed integer in the interval (0,1). $w^{s}_{rand}$is a randomly selected Harris Hawk member from the tth iteration's population. Equally divided random integers in the interval (0,1) are represented by the variables q_1, q_2, q_3, and q_4. The mean rate of the position in the presentpopulace is represented by w^{s}_{mean}, and the lower and upper limits of each variable in the number of individuals are indicated by $ka - va$.Equation (5) shows the computation mode.

$$w^{s}_{mean} = \frac{1}{m}\sum_{j=1}^{m} w^{s}_{j} \quad (5)$$

Shifting from the state of exploration to that of exploitation, the flight power factor (F) is the main factor that controls the HHO algorithm's transition from wide exploration to targeted exploitation. Equation (6) displays the calculating mode.

$$F = 2 * F_0 * \left(1 - \frac{s}{s_{max}}\right) \quad (6)$$

where the random integer F_0 ranges from -1 to 1, and the variables s and s_{max} stand for the iteration's current phase and the highest possible number of modifications, respectively.

Stage of exploitation

Harris Hawks find their target and circle about it, waiting for an opportunity to make a surprise attack. Predators actually have a complicated process because the object of a siege may manage to escape. It will be necessary for a hawk to adjust to the behavior of its prey. In order to more accurately resemble the hunting behavior, four strategies are employed during the exploitation stage.

Soft besiege with gradient fast dives

If both $|F|$ *and* q are less than 0.5, the prey has no possibility of absconding the circle of confinement, but it does have enough energy to do so otherwise, according to the basic algorithm. Hence, Harris Hawks will employ the deceptive besiege strategy when hunting. Equations (7 and 8) can be utilized to symbolize the previous section:

$$w_j^{s+1} = \Delta w_j^{s} - F * \left|I * w_{rabbit} - w_j^{s}\right| \quad (7)$$

$$\Delta w_j^{s} = w_{rabbit} - w_j^{s} \quad (8)$$

Where $I = 2 * (1 - q_5)$represents the prey's leaping length during the escape, $\Delta w_j^{s} q_5$is the vector distance between the optimal individual (prey) in the sample and the current individual, and q_5 is an evenly distributed random value in (0,1).

If the prey possesses the required energy, it may exit the area of encirclement when $|F| \geq 0.5$ *and* $q < 0.5$. Harris Hawks are going to set a more subtle, clever ring of encirclement prior to attacking. The application of this strategy involves two stages. The first step is executed. If, after the initial procedure is finished, the Harris Hawk's location does not improve, the subsequent step's upgrading mode will be applied. Equation (9) offers a mathematical solution for the first phase's methodology. The update mode for the second step is given by Equation (10) as follows:

$$z = w_{rabbit} - F * \left|I * w_{rabbit} - w_j^{s}\right| \quad (9)$$

$$y = z + t * levy(dim) \quad (10)$$

where t is a random vector with a dimension of dim, and dim is the optimization problem's size. Equation (11) defines $levy$.

$$levy(w) = 0.01 \times \frac{v \times \sigma}{|\mu|^{1/\beta}}, \sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right)^{\frac{1}{\beta}} \quad (11)$$

Where the arbitrary values in (0,1) correspond to v *and* μ, and the constant β has a value of 1.5. The conceptual framework for the problem of determining the minimum in optimization is given by Equation (12).

$$w_j^{s+1} = \begin{cases} z, & if \quad e(z) < e(w_j^{s}) \\ y, & if \quad e(y) < e(w_j^{s}) \end{cases} \quad (12)$$

Hard besiege with gradient fast dives

The prey cannot escape and there is not enough escaping energy when $q \geq 0.5$ and $|F| < 0.5$. Harris Hawks will thus hunt using the forceful besiege tactic as presented in Equation (13).

$$w_j^{s+1} = w_{rabbit} - F * \left|\Delta w_j^{s}\right| \quad (13)$$

When q and |F| are less than 0.5, the prey has insufficient energy to flee. The Harris Hawks are currently going to form a solid circle around themselves before they attack. The mathematical framework for a minimum solution optimization problem is given by Equations (14–16).

$$w_j^{s+1} = \begin{cases} z, & if \quad e(z) < e(w_j^s) \\ y, & if \quad e(y) < e(w_j^s) \end{cases} \tag{14}$$

$$z = w_{rabbit} - F * |I * w_{rabbit} - w_{mean}^s| \tag{15}$$

$$y = z + t * levy(dim) \tag{16}$$

3.3.2 Manta ray optimization (MRFO) algorithm

Manta Ray Foraging Optimization (MRFO) utilizes foraging strategies inspired by the natural hunting behaviors of manta rays. These strategies include spiral and circular movements, allowing the algorithm to efficiently search for optimal solutions, mimicking how manta rays navigate through water to find food in their environment.

The manta rays' methods of capturing their prey are imitated by MRFO. MRFO uses three different manta ray foraging techniques: somersault, cyclone, and chain foraging. The process of finding required food is modeled by chain foraging. Foraging manta rays will systematically stretch out and grab any prey that has disappeared or been overlooked by the last manta ray in the sequence.Cyclone foraging occurs when there's a large concentration of prey. The manta ray's head and tail come together to make an arc that borders the cyclone's gaze. Manta rays engage in somersault feeding, where they rotate backward and circle as the prey organisms are moved into their open jaws. Similar to other metaheuristic algorithms, MRFO selects the most desired agent W_{best} with the highest fitness value after defining its initialization to provide random placements for a group of agents W. The three techniques listed above are used to update the agents. The mathematical representations of these tactics are as follows:

Foraging in chains, as described in Equation (17 and 18), is used in this method to update the agent W_l at l_{th}iteration.

$$w_l^{s+1} = \begin{cases} w_l^s + q * (w_{best}^s - w_l^s) + \propto (w_{best}^s - w_l^s) & l = 1 \\ w_l^s + q * (w_{l-1}^s - w_l^s) + \propto (w_{best}^s - w_l^s) & l = 2, \dots, M \end{cases} \tag{17}$$

$$\alpha = 2 * q * \sqrt{|log(q)|} \tag{18}$$

where q is an arbitrary vector in [0, 1], α is the mass coefficient, w_{best}^s is the high-concentration plankton, and w_l^s is the l_{th}location in time l.

Cyclone feeding, as inEquations (19 and 20), is modified in this procedure, updating the agent w_l.

$$w_l^{s+1} = \begin{cases} w_{best}^s + q * (w_{best}^s - w_l^s) + \beta(w_{best}^s - w_l^s) & l = 1 \\ w_{best}^s + q * (w_{l-1}^s - w_l^s) + \beta(w_{best}^s - w_l^s) & l = 2, \dots., M \end{cases} \tag{19}$$

$$\beta = 2.exp\left(q.\frac{L_{max} - l + 1}{L_{max}}\right).sin(2\pi q) \tag{20}$$

With the weight coefficient denoted by β. Moreover, the MRFO's exploration can be enhanced by the cycle foraging step agents' ability to adjust their location in the search space depending on a randomly assigned position. Consequently, the following Equations (21 and 22)are used to update the agent's current location. Where the search space's lower and upper bounds are denoted by the terms Low and Up.

$$w_l^{s+1} = \begin{cases} w_{rand}^l + q * (w_{rand}^s - w_l^s) + \beta(w_{rand}^s - w_l^s) & l = 1 \\ w_{rand}^s + q * (w_{l-1}^s - w_l^s) + \beta(w_{rand}^s - w_l^s) & l = 2, \dots.., M \end{cases} \tag{21}$$

$$w_{rand}^s = Low + q * (Up - Low) \tag{22}$$

Somersault hunting Equation (23) defines the mathematical formulation that was utilized to update the agent in this phase.

$$w_l^{s+1} = w_l^s + t * (q_1.w_{best}^s - q_2.w_l^s) \tag{23}$$

Where q_1 and q_2 are the random values in [0, 1], and s is the somersault component.

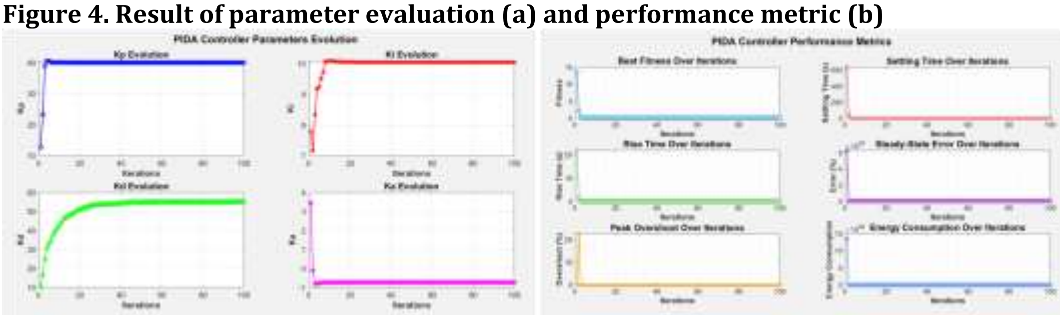
4. Result

The experimental setup requires an operating system of Windows 10 (21H2 or higher), Windows 11, or Windows Server 2022. A minimum of 4 GB RAM is needed, with 8 GB recommended. Storage must include 4 GB for MATLAB and an SSD is strongly advised. A graphics card supporting OpenGL 3.3 is recommended for optimal performance and GPU acceleration.

4.1 Result of 60 bpm heart rate

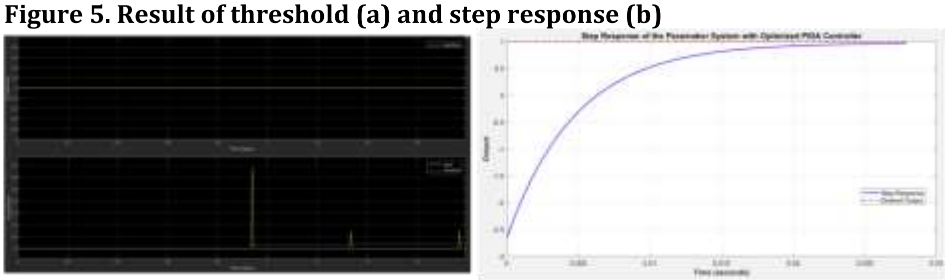
The results for the PIDA controller tuned at a mean heart rate of 60 bpm showcase the evolution of key parameters (K_p, K_i, K_d, K_a) across iterations. The proportional gain (K_p) stabilized within a range of 11 to 40, while the integral gain (K_i) showed convergence from 7 to 10, indicating effective error correction. The derivative gain (K_d) varied from 10 to 50, and the acceleration gain (K_a) evolved from 3, ultimately decreasing to 0, contributing to enhanced system stability. Performance metrics, including steady-state, best fitness, settling time,rise time, andovershoot error were plotted, illustrating the controller's efficiency. Parameter evaluation and performance metrics results are presented in Figure 4. Step response and threshold outcomes are presented in Figure 5.

Figure 4. Result of parameter evaluation (a) and performance metric (b)



(a) (b)

Figure 5. Result of threshold (a) and step response (b)

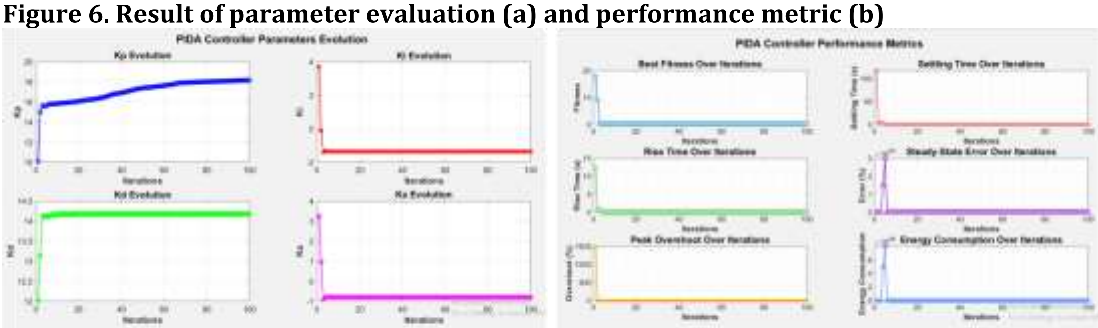


(a) (b)

4.2 Result of 82 bpm heart rate

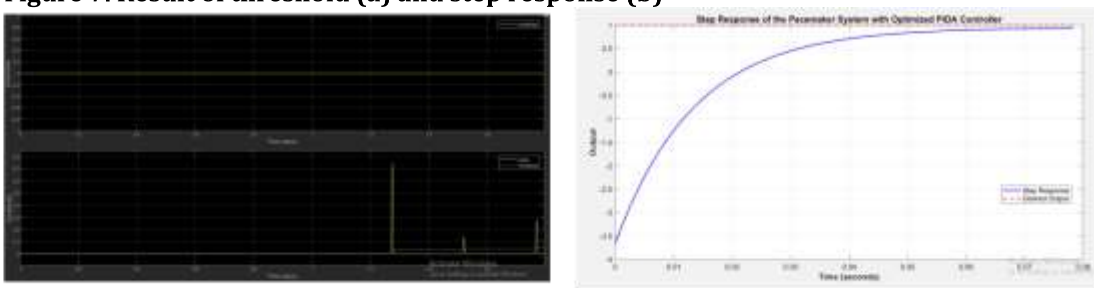
The results for the PIDA controller tuned at a mean heart rate of 82 bpm highlight the evolution of essential parameters (K_p, K_i, K_d, K_a) across iterations. The proportional gain (K_p) stabilized within a range of 10 to 16, while the integral gain (K_i) showed convergence from 4 to 1, indicating effective error correction. The derivative gain (K_d) varied from 12 to 14, and the acceleration gain (K_a) evolved from 3, ultimately decreasing to 1, contributing to enhanced system stability. Performance metrics such as steady-state error,best fitness, settling time,rise time, and overshoot were plotted to evaluate the controller's effectiveness.The results of parameter evaluation and performance metrics are shown in Figure 6. Figure 7 displays the step response and threshold findings.Filtered and raw signal outputs are presented in Figure 8.

Figure 6. Result of parameter evaluation (a) and performance metric (b)



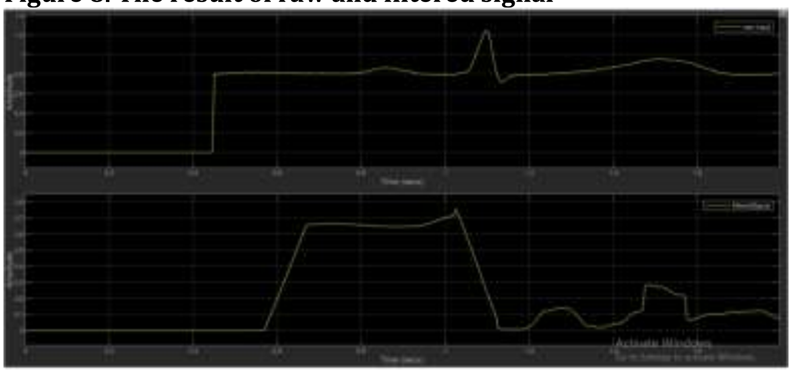
(a) (b)

Figure 7. Result of threshold (a) and step response (b)



(a) (b)

Figure 8. The result of raw and filtered signal



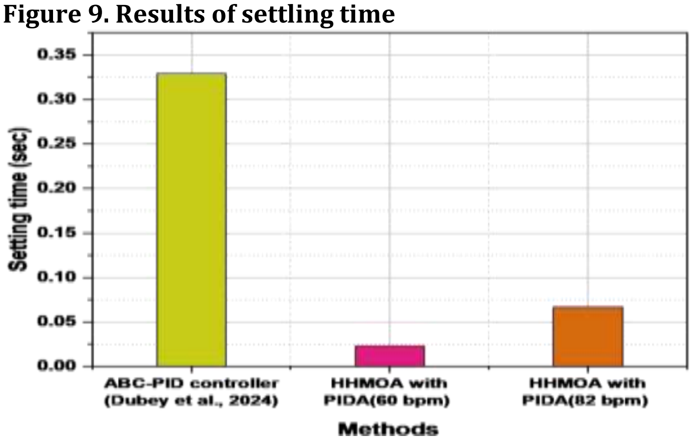
4.3 Comparison Results

The performance of the proposed Hunting Harris-Manta Optimization Algorithm (HHMOA) with Proportional-Integral-Derivative Adaptive (PIDA) controller is compared against the existing approaches, such as ABC-PID controller (Dubey et al., 2024) and Mamdany fuzzy controller (MFC) (Hamed and Ras, 2015), across key metrics: steady-state error, rise time, andsettling time.

Settling Time (Sec)

Settling time refers to the time required for a system to stabilize and remain close to its final value after an input change or disturbance. A shorter settling time indicates quicker stabilization, which is desirable for ensuring smooth and efficient system performance.For the settling time, the existing ABC-PID controller exhibits a settling time of 0.3293 seconds. In contrast, the proposed HHMOA-PIDA controller significantly improves settling time at a heart rate of 60 bpm, achieving 0.0230 seconds. However, at a heart rate of 82 bpm, the settling time increases to 0.0668 seconds, yet showcasing a substantial improvement of the proposed method over the existing approach. Settling time results are presented in Figure 9.

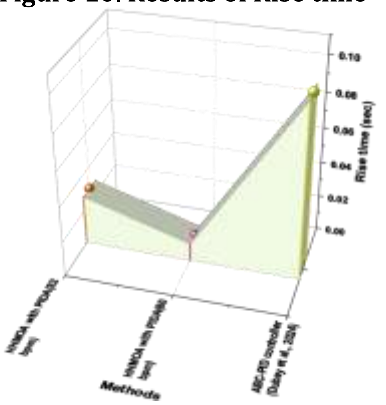
Figure 9. Results of settling time



Rise Time (Sec)

Rise time measures how quickly a system's output reaches its final value after an input change. It represents the system's responsiveness to changes, with faster rise times indicating better performance in reacting promptly to input commands or disturbances.Regarding rise time, the ABC-PID controller has a rise time of 0.0985 sec. The proposed HHMOA-PIDA controller again demonstrates enhanced performance, with a rise time of 0.0101 sec at 60 bpm, and a rise time of 0.0280 sec at 82 bpm. Both values indicate quicker responsiveness compared to the existing method. Figure 10 demonstrates the result of rise time.

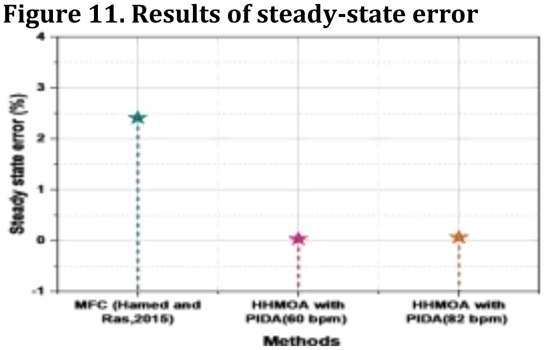
Figure 10. Results of Rise time



Steady-State Error (%)

The disparity that occurs after the procedure achieves equilibrium among the intended and actual output is known as the steady-state error. A smaller steady-state error indicates more precision in sustaining the goal value, guaranteeing a small amount of output variance over time.The steady-state error of the existing MFC is relatively high at 2.41%. The proposed HHMOA-PIDA controller shows remarkable improvement, with a steady-state error of 0.0334% at 60 bpm and 0.0643% at 82 bpm. These lower values highlight the proposed method's greater accuracy in achieving the desired output with minimal deviation. Steady-state error results are presented in Figure 11.

Figure 11. Results of steady-state error



Peak overshoot and Energy consumption

For energy consumption scenarios such as 60 and 82bpm heart beat, the proposed method demonstrates 0.0000% peak overshoot, demonstrating better stability than the existing method with 0.111367% peak overshoot, validating its improved accuracy in control. The proposed method has recorded values of energy consumption of 0.0252 and 0.1005, which indicates better efficiency. The power consumption potential of the existing method is not as comprehensive because it does not provide energy consumption data. The numerical results of key metrics are presented in Table 1.

Table 1. Numerical results of key metrics

Algorithm	Settling Time(Sec)	Rise Time(Sec	Steady-State	Peak Overshoot(%	Energy Consumption

		)	Error(%)	)	
Existing Methods	0.3293	0.0985	2.41	0.111367	-
HHMOA with PIDA (60 bpm)	0.0230	0.0101	0.0334	0.0000	0.0252
HHMOA with PIDA (82 bpm)	0.0668	0.0280	0.0643	0.0000	0.1005

5. Conclusion

The Hunting Harris-Manta Optimization Algorithm (HHMOA) is used to optimize dual chamber pacemaker systems using PIDA control. The HHMOA achieved fine-tuning of the PIDA controller parameters by synergizing HHO and MRFO and achieved notable enhancements in the key performance metrics ofsteady-state error, best fitness, overshoot, settling time,andrise time. The efficacy of the HHMOA in regulating atrial and ventricular synchronization was validated through MATLAB/Simulink based simulations that also suggest its adaptability to different physiological conditions. HHMOA was superior to traditional optimization methods in that it was more precise, had faster response times, and consumed less power, and hence contributed directly to a longer pacemaker lifespan and more reliable heart rhythm management. The hybrid algorithm is shown to significantly reduce heart rate regulation errors and improve system stability, indicating the hybrid algorithm's potential to enhance medical device control systems. The research demonstrated the potential for hybrid optimization techniques in providing precise, robust, and energy-efficient control solutions for dual chamber pacemakers with improved patient outcomes and device longevity.

Limitations and Future Scope: The study primarily focuses on simulations and may not fully capture the complexities of real-world physiological variations. Additionally, the computational demands of HHMOA can be high for real-time applications.Future work could explore real-time implementation, clinical trials, and further algorithm refinement for faster convergence and adaptive control.

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Appendix

DL	Deep Learning	**PCG**	Phonocardiogram
FPGA	Field Programmable Gate Array	**SVM**	Support Vector Machine
BBO	Biogeography Based Optimization	**GA**	Genetic Algorithm
Immune-PID	Immune-Proportional-Integral-Derivative	**AdaBoost**	Adaptive Boosting
TAVR	Transcatheter Aortic Valve Replacement	**bpm**	Beats Per Minute
CAD	Computer-Aided Diagnosis	**CNN**	Convolutional Neural Network
PCM	Cardiac Pacemaker	**ECG**	Electrocardiogram
PPMI	Permanent Pacemaker Implantation	**CVD**	Cardiovascular Disease