Simulation of an Artificial Cardiac Pacemaker*
BENG 122A: Biosystem and Controls

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Abstract—Control systems are largely prevalent across both mechanical and physiological systems. Looking at the intersection between the two, the present work aims to model and simulate the control system of a functioning pacemaker regulating heart rate. The model has been simplified to be a closed loop system that contains the cardiovascular system and a Proportional, Integral, and Derivative (PID) controller with unity negative gain feedback. Tuning was done using MATLAB’s PID controller tuning tool in order to obtain a transfer function that successfully modeled the system with low overshoot, low offset after one second, few oscillations, and a quick rise time. Additionally, an accelerometer was used to simulate a load on the heart that would increase the set point above 60 bpm, such as engaging in physical activity. It was found that the modeled pacemaker system was able to successfully adjust heart rate to these changes in set points. Finally, fuzzy logic based controllers were explored as an alternative to conventional PID controllers. Other literature has cited fuzzy controllers as able to provide better responses for pacemakers.

INTRODUCTION

Continuous operation of the heart is essential for living organisms. Therefore, fail-safe systems are needed to be implemented in individuals susceptible to abnormal heart rhythms. It is important to properly diagnose abnormal hearts in order to remedy the health issue. One of the most common medical devices used to address problems in the natural conduction system of the heart is an artificial pacemaker, which continuously monitors heart rate. These generally have two functional units: the "sensing circuit", which monitors the heart’s natural electrical activity, and the "pacing circuit", which emits an electrical signal to the heart muscles in case the heart’s own rhythm is interrupted or too slow. If a pacemaker senses a natural heartbeat, it will not stimulate the heart. When the HR drops too low (bradycardia) or goes too high (tachycardia), the pacemaker senses the abnormal HR and sends an electrical excitation signal to the heart muscles, which forces the heart to contract at a fast/slow enough rate to maintain a normal rhythm. The leads of a pacemaker can be positioned in the right atrium, right ventricle, or both, depending on the diagnosed heart condition. Figure 1 shows the heart location and pacemaker connection to the heart chambers.

Previous work have modeled the control system of the heart to bring it back to normal conditions. For example, Biswas et al. used a transfer function method to mathematically model the cardiovascular system [2]. In another paper by Inbar et al., they used a proportional and integral controller to design a closed loop pacemaker for regulating the mixing venous oxygen saturation level [3]. Work by Shin et al. and Wojtasik et al. studied rate-adaptive artificial heart pacemakers using fuzzy logic controllers [4].

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\textsuperscript{1}These authors contributed equally to this work.
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![Image](image-url)
Sugiura et al. concluded a fuzzy approach was the best to control heart rate using a pacemaker regulated by respiratory rate and temperature [6]. Jyoti et al. compared a fuzzy controlled and a PID controller tuned with Ziegler-Nichols, Tyreus-Luyben, and Relay methods; the work simulated and demonstrated that the fuzzy controller had a maximum overshoot less than all of the tuned PID controllers and improved rise time and settling time than at least two of the three tuning methods [7]. However, because of the complications regarding learning and implementing a fuzzy control system, we have chosen to use a PID controller and will explore fuzzy controllers as a future goal as it showed significantly better responses from the previous literature.

The general process of how a pacemaker works is as follows: a heart rate input is continuously measured by the electrodes, which is amplified by a low noise pre-amplifier; it is filtered by a second order low pass filter to obtain the appropriate ECG; the signal and a threshold detector is sent into a comparator; the comparator output is processed in a low power microcontroller where an electrical output is multiplied and sent to the heart via a pacing pulse generator and pacing electrodes. Lithium iodine batteries are used for the power supply and a supply voltage supervisor (SVS) is incorporated to monitor battery life. The pacemaker schematic is summarized in Figure 5.

In the work presented here, we briefly explain the heart’s electrical system and the pacemaker-heart interaction. Assumptions were made to isolate the control system, as the entire cardiovascular system is too complex to model in a simplified, yet relevant, manner. We then present a modeled control system of the pacemaker response to a discrete impulse, unit step, and dynamic signal. Finally, fuzzy logic controller was explored for future work, as previous literature has shown it has a better response than a PID controller. Lastly, the behavior of the system was analyzed with a frequency response and a stability analysis.
the impulse affects neighboring cells, a chain reaction is activated, spreading to the Bachmann’s Bundle in the left atrium within 0.2 seconds and the atrio-ventricular (AV) node shortly thereafter. The signal travels from the AV node to the ventricle walls through the His bundle and spreads down to the Purkinjie fibers. Summarizing the chambers that receive the electrical signal are right atrium, left atrium, right ventricle, and left ventricle. These electrical conduction pathway is what controls the relaxing and contracting of the heart to pump blood. Completion of this step-by-step process produces a full cycle and is known as one heart beat. However, aging or heart diseases may cause damage to the SA node’s ability to properly pace the beat of a heart, resulting in slower, faster, or paused beats. Pacemakers are introduced to these types of heart problems in order to sync the heart as close as possible to its natural heart rate.

**B. Pacemaker-Heart Control System Model**

The pacemaker is an electronic device that can regulate the human cardiovascular activities in the case of bradycardia and tachycardia or in general when the heart natural regulating mechanisms collapses. The pacemaker is made of various parts, including the casing, microelectronics, and the leads which are all made with biocompatible materials. Modern pacemakers also use accelerometer, impedance and force detectors in order to adjust the pacing pattern with the patient’s activity level. Pacemakers operate under two main modalities:

- Sensing Modality
- Pacing Modality

Sensing Modalities: Blended sensors: Combination of accelerometer, minute ventilation (breathing patterns) and cardiac contractility sensor. Accelerometer provides immediate response at beginning of sudden fluctuation in physical activities while minute ventilation offers a gradual response to the disturbance, detects increased metabolic need and adapts pacing rate accordingly. In other words, this sensors predict whether the individual is sleeping, having normal activity or is working out and adjust the heart rhythm accordingly. The lead’s electrodes are also able to sense contraction force of the ventricle’s chambers and predict how fast heart needs to contract in order to maintain the cardiac output Figure 6.

- Pacing Modality: Pacemakers electrodes can attach directly to the ventricles, or atria (Single chamber) or both (Dual chambers) depending on the patient’s medical situation. Pacemakers
can also be used as a monitor to track and control different abnormalities such as pausing or cardiac arrhythmia.

II. ASSUMPTIONS

In order to simplify the cardiovascular system and the pacemaker-heart interaction, a few underlying assumptions were made. Our simulation and results presented later hold true based on the following:

- Biocompatibility
- Ideal Heart
- Lead placement never disturbed
- Accurate Sensors
- Zero Latency
- Pacemaker is always on
- Isolated Single Chamber Pacing

When the body identifies something as a potential hazard it will act accordingly to maintain homeostasis. For example it might increase blood pressure to induce clotting and white blood cell presence, both of which could negatively impact the pacemaker system. Biocompatibility ensures that the artificial cardiac pacemaker is accepted by the body without inducing abnormal side effects. The heart is also assumed to have a constant resistance throughout the tissues that the pacemaker acts upon so that the electrical signal propagates as intended. The heart's conductive component was simplified to a simple circuit because the heart transfer function that was acquired from literature did not take that into account [7]. Our model is unable to account for physiological complications, so anything that hinders electrical signal propagation is also not taken into account.

Pacemakers are generally only used to treat bradycardia, as such the model only responds when the patient's heart rate is lower than the desired range. Only the actual pacing itself is analyzed, therefore we are assuming that the sensor portion of the pacemaker works properly. The leads have to have good connection to accurately relay signals between the heart and the pacemaker. During a case in which the sensor detects an inaccurate heart rate, the pacemaker could either adjust the heart rate too high, too low, or have no response when pacing is necessary. Atrioventricular synchrony is the natural heart activation sequence in which the atria and then after a normal delay, the ventricle contracts [11]. The disruption of this natural rhythm is an inherent side effect of single chamber pacemakers and can be fixed with an atrial lead to optimize AV synchrony if found necessary. Adverse side effects of AV dissynchrony have not been significantly studied, and therefore the optimization to account for it is left out of the system.

The lag or latency inherent within the system is ignored. Lag would result in a significant time delay between the sensing of the current heart rate and the actual contraction of the heart after the artificial signal is transmitted to the AV node. The heart rate transmitted from the pacemaker could differ from what is actually needed, and could lead to complications within the heart.

The model is based on the assumption that the sensor is working properly and that the pacemaker is already turned on. The accelerometer detects the heart rate, and only signals the pacemaker to turn on when necessary. What is modeled is the response of the system after a disturbance has been detected. The model focus is the pacemaker response and how the fuzzy logic controller makes for an ideal method of controlling heart rate. Therefore the accelerometer or the sensing aspect of the system is absent for simplification.

In addition, the single chamber that we are pacing is isolated from the outside world. We are also assuming that the pace of that chamber is representative of the entire heart.

III. MODELING

A. General Overview

Using the assumptions previously made, a simplified version of a model for a Pacemaker-Heart system with an input signal from an accelerometer

![Fig. 7. General block diagram of Pacemaker - Heart interaction control system [7].](image-url)
can be built. The model includes a load which acts on an accelerometer, a set heart rate at which the pacemaker will pace, a Pacemaker, a PID Controller, and the Heart, which can be modeled in terms of its cardiovascular function and its electrical conductive properties. Such a model is shown in Figure 8. A set point is chosen and fed into the Pacemaker-Heart closed loop system, which outputs the heart rate at which the heart is beating. For this model, the set point was chosen to be 60 beats per minute (bpm). In addition, a disturbance can be introduced into the system by acting on an accelerometer, which feeds its response into the Pacemaker-Heart system to increase the heart rate set point with an increase in physical activity or movement. A lag was also introduced into the system to model the time delay of the accelerometer.

**B. Pacemaker-Heart Model**

A closed-loop system for the heart, pacemaker, and PID Controller is shown in Figure 7, where \( G_p(s) \) is the transfer function of the pacemaker, \( G_c(s) \) is the transfer function of the PID Controller, and \( G_H(s) \) is the transfer function modeling the cardiovascular function of the heart[7]. The transfer function for the pacemaker and the heart are shown in Equations (1) and (2), respectively. This model did not include the electrical conductive properties of the heart, which we modeled after Ohm’s Law and added to the system shown in Figure 8. The governing equation for the heart’s conductive properties is shown in Equation (4), where \( R \) is the electrical resistance of the heart’s conductive pathways, \( V \) is the voltage of the Pacemaker’s battery, and \( I \) is the current running through the heart. For this system, the values for \( R \) and \( V \) were determined to be 100 \( \Omega \) [12] and 2.8 V, respectively. The component \( H(s) \) in Figure 7 represents the feedback gain, which was set to 1 to keep the output signal unaltered as it is fed back to the system. If the feedback gain was a value other than 1, the hear rate at which the heart was pacing would be altered, and the controller would fail to drive the heart rate at the pace set by the system’s input \( R(S) \), which will be the heart rate at which we want the Pacemaker to pace the heart. The output \( Y'(s) \) will be the heart rate of the heart in beats per minute.

The transfer function of the pacemaker is that of a first order system with \( \tau = 1/8 \) and a steady-state gain of \( K_{ss} = 1/8 \). From this, the cutoff frequency \( \omega_c \) of the pacemaker can be determined to be \( 1/\tau = 8 \). This is important, given that the Pacemaker itself acts as a low-pass filter, preventing high frequencies signals from being transmitted to the person’s heart. This is a safety feature that is desirable in pacemakers.

\[
G_p(s) = \frac{8}{s + 8} \tag{1}
\]

\[
G_H(s) = \frac{169}{s^2 + 20.8s} \tag{2}
\]

\[
G_c(s) = K_c(1 + \tau_D s + \frac{1}{\tau_I s}) \tag{3}
\]

\[
I(s) = \frac{V}{R} \tag{4}
\]
C. PID Control

The transfer function for a Proportional-Integral-Derivative Controller is shown in Equation (3). In the expression, $K_c$ is the proportional gain, $\tau_D$ is the derivative time, and $\tau_I$ is the integral time. These parameters can be altered to obtain a desired controller response. The parameters affect the closed loop system’s rise time, overshoot, settling time, and steady state error. The PID Controller in the close-loop portion of the model should be able to accomplish two goals:

1) It should be able to drive the pacemaker to pace the heart at the desired rate in a short amount of time after the system is initiated.
2) It should reach the set point without showing a strong oscillatory or overshoot response.

The first goal of the model is desirable given that a pacemaker should start pacing a person as soon as their heart stops beating by itself. In other words, the pacemaker should not take as long as a minute or two to bring the heart rate to 60 bpm. To achieve this, the rise time and settling time of the response have to be decreased. The second goal is desirable given that the pacemaker should not cause the person’s heart to beat at a high pace, followed by a very low pace, or simply beat at an excessive pace. If the system’s response oscillates, the patient’s heart could be driven to beat at 100 beats per minute one second, and at a 40 beats per minute pace the next. If the overshoot of the system is large, the patient’s heart could be paced at 140 bpm for a short time before it settles. We decided to implement a PID Control in our system given that we want to decrease the settling time of the system’s response, decrease the oscillations of the system, and have a fast rise time. A proportional and integral control can help decrease the rise time, and the integral control will help eliminate any offset from the set point at steady state. The derivative control will help decrease the overshoot and the settling time of the signal. The PID Controller’s parameters were tuned using MATLAB’s PID Controller Tuning Tool to obtain a desired system response. The Controller’s parameters and further explanation on how they were obtained can be found in the Heart Rate Controller Section of this paper (Section IV).

D. Accelerometer

An accelerometer’s internal components can be expressed as a spring-mass-damper seismic structure with a strain gauge to convert a physical movement into a voltage [13]. Such a system is depicted in Figure 9, where $k$ is the spring constant, $m$ is the mass, $b$ is the damping coefficient, $x$ is the position of the mass, and $V_0$ is the output voltage of the strain gauge. From Newton’s Laws, a differential equation can be derived, and transformed into the s-domain to obtain the transfer function of the accelerometer. Equations (5) and (6) show the differential equation and its Laplace Transform, respectively, where $\omega_n$ is the natural frequency of the system and $\zeta$ is the damping coefficient. The time constant $\tau$ could also be used to model the system, given the relationship $\tau = 1/\omega_n$. When a strain gauge is used to determine the displacement of the mass inside the accelerometer, Equation (6) can be rewritten as Equation (7), where $V_o$ is the output voltage of the strain gauge, and $S_x$ is the sensitivity constant of the gauge in volts per units of displacement.

\[
\ddot{x} + 2\zeta\omega_n\dot{x} + \omega_n^2x = \ddot{u} \quad (5)
\]

\[
\frac{X}{U} = \frac{1}{\frac{1}{\omega_n^2}s^2 + \frac{2\zeta}{\omega_n}s + 1} \quad (6)
\]

\[
G_{Acc}(s) = \frac{V_o}{U} = \frac{S_x}{\frac{1}{\omega_n^2}s^2 + \frac{2\zeta}{\omega_n}s + 1} \quad (7)
\]

Equation (7) shows that an accelerometer acts as a second order system, with a system damping coefficient $\zeta = b/2\sqrt{km}$ and a natural frequency $\omega_n = \sqrt{k/m}$, which can be tuned by selecting appropriate values for the mass, spring constant.
and damper damping coefficient. Ideally, the accelerometer should exhibit a behavior close to that of a perfectly damped response so that it can accurately measure changes in motion, and the lack thereof. For example, if a person stands up from a sitting position, the accelerometer should record a sudden change in movement, followed by a quick stabilization to show that the patient has stopped moving. To accomplish this, the damping coefficient $\zeta$ should be slightly less than 1. If $\zeta$ was given a value much smaller than 1, the system would be under-damped, meaning it would oscillate; oscillations would mean that the accelerometer would be modeling motions that are not happening, given that it would display overshoot and oscillatory behavior. If $\zeta$ was much greater than 1, the accelerometer would be over-damped, and it would not register changes in motion fast enough to readjust the patient’s heart rate. For example, if a person stand up, the pacemaker should increase the heart rate immediately, not 10 seconds after they stand up. Although a value of 1 for $\zeta$ would mean that the system was critically damped, we want our system to respond faster than a critically damped system, even if this results in some overshoot and oscillations. For this reason, our value of $\zeta$ was chosen to be smaller than 1, which resulted in a smaller rise time, at the cost of a small overshoot. We decided it would be better for a pacemaker to pace a heart at a slightly faster pace for a few seconds than to have a delayed response in which the accelerometer’s signal would take too long to model a change in motion.

To determine the exact value of $\zeta$, we first determined the natural frequency of the system, which determines the cutoff frequency of the accelerometer. Modern accelerometers can use computer algorithms to analyze the response of the device and make decision to determine any change to the set point at which to pace the heart. Our model cannot use any of the algorithms, but we can use the accelerometer’s cutoff frequency to prevent the device from sensing high frequencies, and pacing the heart at those frequencies. For example, if a person with an accelerometer goes on a run, the pacemaker should not increase and decrease their

<table>
<thead>
<tr>
<th>Fast Response</th>
<th>P</th>
<th>I</th>
<th>D</th>
<th>Overshoot</th>
<th>Rise Time</th>
<th>Offset (at 1 sec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Some Oscillations</td>
<td>161.151</td>
<td>56.561</td>
<td>102.0163</td>
<td>42%</td>
<td>0.03</td>
<td>0</td>
</tr>
<tr>
<td>No Oscillations (slow response)</td>
<td>22.1479</td>
<td>18.9973</td>
<td>2.8265</td>
<td>18.3%</td>
<td>0.35</td>
<td>5</td>
</tr>
</tbody>
</table>

TABLE I
SYSTEM CHARACTERISTICS FOR VARIOUS PID CONTROLS
Therefore, the lag transfer function delays smaller than .01 seconds, approximately. Simulink was unable to solve the system for time due to numerical solver complications. However, the second order Padé approximation had to be removed from the final Simulink model of the system. The transfer function for a second order Padé approximation was used. The transfer function was chosen when a dynamic signal acts on the system. Having chosen \( \omega_n \) to equal 1/2, we can determine that if \( \zeta \) was given the value of one, the first order coefficient in the characteristic equation of the accelerometer’s transfer function would equal 4 \( (\frac{2}{\sqrt{5}}) \). Given that we want a value of \( \zeta \) lower than one, we arbitrarily chose 3.4 as the first order coefficient in the characteristic equation of the accelerometer’s transfer function, resulting in a \( \zeta \) value of 0.85, keeping in mind the trade-offs between a faster rise time and system oscillations.

The sensitivity of the accelerometer \( S_x \) can be selected to obtain a desired steady state gain of the system when a step input is applied to it. In the case of our system, we want to establish a maximum steady-state heart rate of 120 bpm, so we will use a sensitivity \( S_x = 60 \) assuming a step input, given that the signal from the accelerometer will add to the set point to result in a heart rate of 120 bpm.

To account for a time delay associated with the accelerometer’s response, a time lag of 0.38 ms was included into the system shown in Figure 8. To include the time delay in our system, a second order Padé approximation was used. The transfer function for a second order Padé approximation of a time lag \( e^{-\tau s} \) is shown in Equation (8).

\[
G_{P'a'd}^2 = \frac{1 - \frac{5}{7} s + \frac{\tau^2}{12} s^2}{1 + \frac{5}{7} s + \frac{\tau^2}{12} s^2}
\]  

(8)

Unfortunately, the time delay of the accelerometer was much smaller than the time constants of the rest of our system, which were in the order of magnitude of \( 10^0 \), compared to the order of magnitude of the delay of \( 10^{-5} \).

E. Simulink Model

With all the above components taken into consideration, a Simulink model of the system in the s-domain was built, which is shown in Figure 10. The model also includes a Time Scope that was used to observe the system’s output, as well as the output of the accelerometer. The overall transfer function of the system is shown in Equation (10), where the set point \( SP(s) \) is a constant heart rate at which the pacemaker will drive the heart, and \( U(s) \) is a load on the accelerometer.

IV. HEART RATE CONTROLLER

In this section three different PID controllers with various characteristics are introduced to the model. The PID controllers were tuned using the PID tuning tool in Simulink to obtain three distinctly different responses. The tool allows the user to adjust the response time and how aggressive or robust the transient behavior is. The tuning tool provides parameters \( P, I, D \) and \( N \) for Equation (9), which is a standard PID with a filtered derivative.

\[
P + I \frac{1}{s} + D \frac{N}{s + N^2}
\]

(9)

The parameters \( P, I, D, \) and \( N \) represent the Proportional control, Integral control, Derivative control, and Derivative Filter coefficient for the system, respectively. The response of PID controllers are characterized by three quantities: overshoot, rise time, and offset. The overshoot represents the initial jump in heart rate relative to the set point before the system starts to settle; the rise time tells you how long it takes for the system to converge; and the offset is the difference from the set point in beats per minute once the system converges. Two models were tuned to either reach the set point fast at the expense of a high oscillatory motion and overshoot or to minimize the overshoot, at the cost of a longer convergence time plotted as responses 2 and 3 respectively in 11. Our goal from the tuning was to find a safe balance between overshoot, oscillation, and rise time, which was
\[ Y(s) = \frac{G_p(s)G_c(s)G_H(s)I(s)}{1 + G_p(s)G_c(s)G_H(s)I(s)}SP(s) + \frac{G_p(s)G_c(s)G_H(s)I(s)G_{Acc}(s)G^2_{pad}U(s)}{1 + G_p(s)G_c(s)G_H(s)I(s)} \]  

V. SIMULATION RESULTS

To test the Simulink model of the Accelerometer-Pacemaker-Heart system, three different load signals were used. For all simulations, the set point of the system was set to 60 beats per minute, as previously mentioned. The load inputs used were a discrete input with a pulse duration of 0.5 seconds, a unit step input, and a sinusoidal wave of varying frequencies. In addition, a time delay was added to the accelerometer’s signal to depict the response of the system when the Pacemaker is turned on, and a separate response of the system when a disturbance acts on the system.

A. Discrete Impulse Input

Fig. 12. System and accelerometer response to a discrete impulse of 0.5s duration.

Fig. 13. System and accelerometer response to a discrete impulse of 0.5s duration with a 6s delay.

The accelerometer and model’s responses to a discrete impulse with a duration of 0.5 seconds are shown in Figure 12. This input load was used to model a scenario in which a person stands up, and the heart rate must increase to account for an increase in pressure resulting from the motion
of standing up. If a person’s heart rate does not increase when they stand up from a sitting position, the increase in pressure can decrease the flow of blood to the brain and make them faint. The system response in Figure 12 shows that the heart rate at which the device drives the heart does increase when a discrete impulse acts on the system, as it should. In addition, Figure 13 shows the responses of a discrete step impulse of equal duration, but with a time delay of 6 seconds. In this Figure, it is evident how the accelerometer’s response is added to the overall system response. The magnitude of the accelerometer’s response is not 60 bpm, which was selected as the accelerometer’s sensitivity so that the maximum heart rate at which a heart could pace would be 120 bpm. The actual magnitude of the accelerometer is closer to 5 bpm. The reason for this was that the accelerometer’s response was unable to fully respond to the signal in the 0.5 second duration of the pulse. From this observation, it can be said that the change in heart rate resulting from a discrete impulse will be dependent on the duration of the impulse. Longer pulse durations will result in higher output heart rates.

**B. Unit Step Input**

The response for the accelerometer and system when a unit step load acts on the model is shown in Figure 14. A unit step input was used to model a scenario in which a person with a pacemaker is undergoing a constant physical exertion that results in constant changes in motion. For example, if a person with a pacemaker goes on a run, the accelerometer would register constant changes in motion. As a result, the pacemaker would drive the heart at a higher rate, just as a healthy heart would increase its beating frequency to increase the cardiac output to deliver more blood to the body. If the system did not show an increase in heart rate, the patient would not receive enough oxygenated blood throughout their body, and would be unable to withstand prolonged physical exertions. As was mentioned earlier, the sensitivity of the accelerometer $S_x$ was chosen to be 60 so that the maximum heart rate during prolonged physical exertion would be 120 bpm, which is the heart rate shown in Figure 15, which shows the system’s response to a step input with a time delay of 6 seconds, showing the individual responses of the system when the pacemaker is turned on, and when the accelerometer senses a disturbance.

**C. Sinusoidal Dynamic Wave Input**

The unit step input showed that the accelerometer could register a constant change in motion, and output a corrected heart rate to provide the body with proper oxygenation. However, it would be unlikely for an accelerometer to register a constant change in motion for a prolonged period of time. For this reason, a dynamic signal was used to drive the model and test how it responded to sinusoidal inputs of different frequencies. The magnitude of the dynamic signal was used to drive the system, given that any motion registered by the accelerometer, either in the positive or negative direction,
should result in an increase in heart rate. Figure 16 shows the response of the system to a sinusoidal wave input with frequency equal to 1Hz, which attempt to model the movement of a person as they run. The Figure shows that the accelerometer’s cutoff frequency removed the dynamic component of the signal, and drove the pacemaker to pace the heart at a constant heart rate, which was what the accelerometer was designed to do. Figure 17 shows the system’s response to a dynamic signal of frequency 0.02 Hz. A signal of this nature would model a person sitting down and standing up several times. The accelerometer did not filter out the signal nor did it attenuate it, given that it was below its cutoff frequency.

D. Physiological Complications and Device Malfunction

To further test the Simulink model, the resistance of the heart was set to $10^{15}$ to model an Atri-ventricular (AV) Block, which is characterized by the decrease in conduction of the heart’s electrical pathways. The increase in resistance was used to simulate a decrease in conduction. Figure 18 shows the results of the simulation, which show that for high resistances, the output heart rate goes to zero, even when the accelerometer registers a signal, as shown by the second trace on Figure 18. The exact same results were observed when the voltage of the pacemaker’s battery was set to zero in an attempt to model a scenario in which the pacemaker’s battery would run out of power. As expected, the output heart rate was 0 bpm, given that the pacemaker was unable to pace the heart without a power source.

E. Frequency Response

A frequency response analysis was performed on the overall transfer function given in Equation 10. The Bode plot in Figure 19 shows an underdamped response with a -40 dB/decade slope and a peak in magnitude at the cutoff frequency, as expected of an underdamped system. For the phase plot, we can see a very steep rise at the cutoff frequency, which is also characteristic of an underdamped system. At low frequencies, a phase shift of -360° is seen, as well as a phase shift of -270° at high frequencies.
Stability Analysis

Stability analysis was also performed on the overall transfer function Equation 10. Figure 20 shows the Nyquist behavior of the system. A zoomed-in version on the real axis at -1 is shown in Figure 21. This shows the plot going around -1, rather than encircling it. Hence, the system is stable.

An alternative controller to PID is a fuzzy control system. Fuzzy control systems are very primitive compared to PID control systems. What makes a fuzzy controller unique is that it runs on Fuzzy logic rather than Boolean logic. That is to say instead of categorizing data based on truths (i.e. good/bad, 0/1), fuzzy logic categorizes on partial truths (i.e. very good/good/bad/ very bad, [0,1]).

Additionally, rather than being a computational type of model, the fuzzy model is based on empirical rules (almost like trial and error). Because of this the behavior and design of a fuzzy control system is drastically different from that of a PID [15].

Fuzzy control systems function on three main interfaces [16]:
1) Fuzzification
2) Decision Making
3) Defuzzification

Fuzzification refers to the idea of taking an input, like temperature, and making the “crisp” raw temperature value into a “fuzzy” value indicates by more categories then simple “Hot” and “Cold”. Figure 22 is an example of such an input.

In Figure 22, the x-axis represents temperature while the y-axis represents the membership function (MF) value. Each color triangle is a MF and the corresponding category title along the top (Cold,
Cool, Nominal, Warm, and Hot) represents the associated fuzzy value. The strength in the fuzzy system is seen by the fact that different categories intersect with each other. What this signifies is that no temperatures do not belong exclusively to one category. Instead, they are in multiple categories but to different degrees. A way to conceptualize this is that at any temperature, some people can view the temperature one way while others another. The idea is that at no point does an input value instantaneously flip from one characterization to another (unless it is something like a switch). More often, as an input value transitions it becomes less like one category, and more like another. The categories used in Fuzzification comes from the operators and human who understand the physical, mechanical, or physiological system to be modeled. In order to assign a final single value for an input that falls into two categories, the centroid method is used in order to properly weight how much the input value falls within one category or another. Other methods exists, but the baseline standard is the centroid method [17].

Following fuzzification is the decision making process. The decision process is where all fuzzified input values are compared with each other to yield a final fuzzy decision. The rules that dictate this decision process are “If...Then...” statements that model the desired outputs for all scenarios of possible inputs. These rules are defined by human experiences and knowledge of how the process works. A sample rule for multiple inputs would read “If temperature IS cool AND pressure IS strong, THEN throttle is FuzzyValue”. Key words such as AND, OR, and NOT dictate how fuzzy values relate to each other and thus influence the FuzzyValue [15].

The final step of the fuzzy control system is defuzzification. Through this process, the determined fuzzy result is converted back to a usable “crisp” output value that can be used in the control system [16]. Figure 23 shows MF mapping for a system with 2 inputs and a single output and Figure 24 shows the overall model of a fuzzy controller. It is important to notice that the Fuzzy Controller diagram shows a knowledge base consisting of of two categories "Data Base" and "Rule Base". "Data Base" is the user knowledge that determines the categories when the fuzzy controller is being designed and "Rule Base" is the "If... Then..." rules the controller designer implements.

Despite being far older than PID controllers, the fuzzy controller has a few major benefits that make it a good option for cardiac pacemakers. First, with regards to design, Fuzzy logic builds off of terms of the human operators and their experiences. This aids in mechanizing the tasks that have already been done successfully by humans. A second benefit is that fuzzy control systems work well for models that are either too computationally heavy or do not exist. Third, fuzzy controllers are relatively low cost compared to PID controllers as the resolution does not need to be as high. Last, more rules and inputs can easily be added to fuzzy controllers in order to improve the robustness of the systems. For these reasons, adding a fuzzy con-
troller would be a strong next step for developing the device [15] [7].

VII. LIMITATIONS

Limitations of the model designed are derived from our simplifying assumptions of the heart and pacemaker. Limitations, likewise stem from the confines of our MATLAB model and can be reflected in simulations.

With regards to an actual pacemaker, the structure has been heavily simplified. First, PID controllers are used in our system opposed to fuzzy controllers. PID controllers work on discrete values while Fuzzy uses partial truths, which better describes the actual functionality of the heart. Second, there are a lot of different modalities that affect heart rate like contractility and ventilation patterns. We have only considered physical motions that can be detected by accelerometer. Third, Modeling a pacemaker solely from transfer functions makes the system unable to perform heavy computational analysis of inputs. Current pacemakers are far more complex than a simple set of controllers and better resembles the capabilities of a full scale computer.

Looking at the physiology, we have assumed the heart to be a simple circuit with a single constant resistance. This is inaccurate as resistance in the heart is actually dependent on ion movement and ion channels. Extra-cellular and intra-cellular ion concentrations are constantly changing which impacts ion flow, and thus the current and resistance of the heart. Modeling the system with a constant resistance prevents the ability of the system to account for physiological syndromes that impact ion flow. Additionally, we have only modeled the heart as single chamber. This means that the frequencies of other chambers are being ignored. In some cases, AV dissynchrony, such a model can translate to the disruption of the heart’s natural rhythm.

Last, the Simulink model and transfer function for our system were found to have inherit limitations. Within Simulink, the MATLAB solver was unable to determine the second order padé approximation of our time lag of 0.38 ms. Because of this it was excluded from or simulations. For our transfer function, a load of zero was assumed so that a transfer function could be attained relating our output to our input set point. However, this is never the case in reality as the accelerometer, which measures our input load, will always have a reading.

VIII. DISCUSSION

Our simulation of the pacemaker in response to a load in heart rate changes does not serve as a strong alternative to physiological experimentation. This is because our model oversimplifies both the physiology of the heart as well as the intricacies of a pacemaker as previously mentioned in the limitations.

Our simplifications make the pacemaker we designed only valid if assuming all variables, aside from changes in motion measured by the accelerometer, to be constant. Physiological experimentation however will take into account all existing factors.

IX. FUTURE WORK

Continuing forward with this project, it is necessary to explore the details of using a fuzzy controller either as the single control system or in conjunction with a PID controller. PID controllers alone requires a lot of assumptions, sometimes oversimplifying the problem at hand. Fuzzy controllers are based around a foundation that because of such assumptions, we can not be 100 percent certain of inputs, and thus define inputs as partial truths rather than absolute truths as seen by the overlap in their characterizations and use of membership functions.

While a fuzzy control system cannot perfectly map a full system because it is empirically based rather than computational, more and more inputs can always be added to enhance robustness and create at times a more accurate model than one that is purely computational.
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