Control of an Unknown System as it Relates to Smart Thermostats

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1 Introduction

Control engineering is the process of designing systems that converge to desired outcomes. The goal of this project is to model the transfer function of an unknown system, design a controller for it, and then apply that controller to the black box. First, the transfer function of the black box was modeled. This involved filtering techniques, Bode plots, and examining properties of the transfer function. Second, a controller was developed for the system that steered the output of the black box to step input within a certain tolerance.

Next, the application of such a controller to thermostat temperature control was explored. Parallels were drawn between the technical process and the physical application. Among other areas, social, environmental, and economic impacts of such technology were explored and discussed.

2 Technical Process

2.1 Modeling

The initial approach to this project was to simply test the black box with a variety of functions and observe the outputs. By using combinations of sinusoids, polynomials and exponentials, crude observations were made that the output function was noisy, phase shifted, and had a change of amplitude that depended on frequency. Clear noise patterns and output trends were seen when the step size of the black box graphical user interface (GUI) was decreased, as seen in Figure 1.

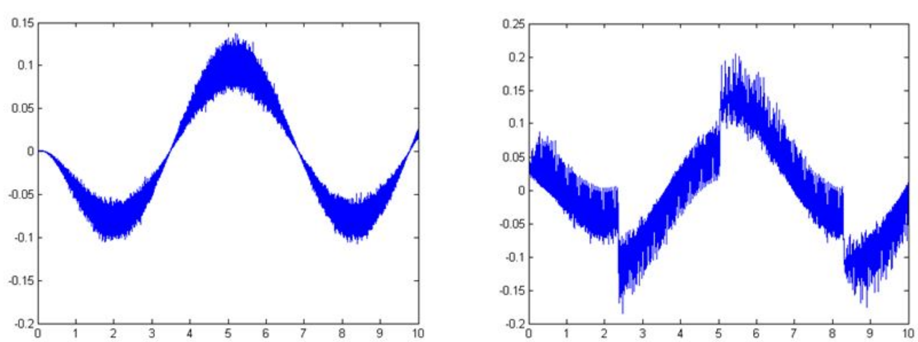

Figure 1: Demonstrated effect of decreasing the step size by a factor of 100.

The next step of the process was to confirm linearity and time-invariance of the black box system. The tests for these properties are as follows:

Linearity: Show that for any f_1 and f_2, and real numbers a, b:
$$T(af_1 + bf_2) = aT(f_1) + bT(f_2)$$
Time invariance: For any function f and real number a:
$$T(f(t + a)) = T(f(t) + a)$$

These two properties were confirmed by trial and inspection of the outputs. Two different sets of test functions were used to check each property; however only one is illustrated in Figure 2 and Figure 3. The phase shifts, scaling, and homogeneity were all simply observed graphically. This was deemed to be sufficient validation because the applied tests were performed with large scaling and phase shifts that did not require precise measuring of the results. Furthermore, the system was being checked for LTI behaviour rather than strictly being an LTI system which allowed for further leniency. This is an assumption that linearity and time-invariance will hold for all functions if it holds for a small subset of functions. This is not as rigorous as it could be, since there is a chance that linear results could be meeting our requirements by coincidence.

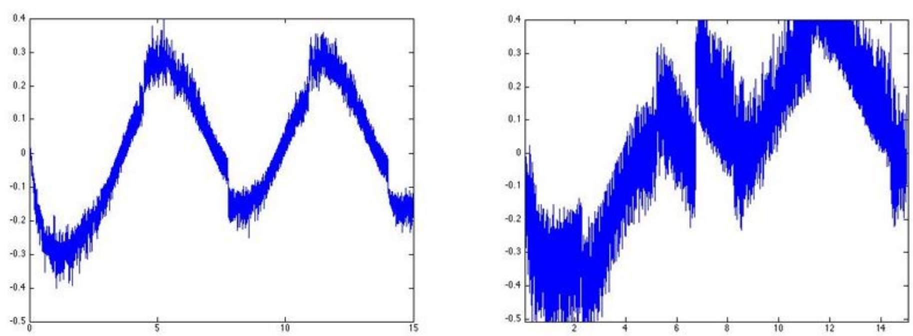

Figure 2: Composition of functions to show linearity.

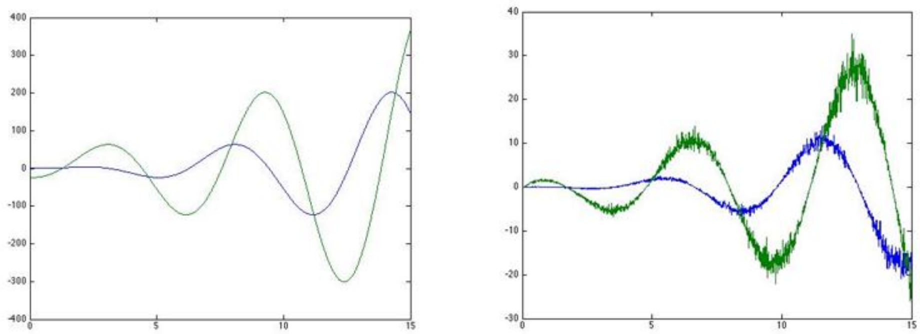

Figure 3: Shifted functions to show time-invariance.

To check linearity we first entered Function 1 into the `blackBox` Function. Function 2 and Function 3 were then entered separately. Once data was saved for each plot, both sets were multiplied by the appropriate constants and then added together. By comparing the plot to the original `blackBox` output, linearity for these functions was confirmed. Upon visual inspection, the combined graph has more noise than the original, but the trends are the same.

$$\text{Function 1: } f_1 = 3t + 5cos(t)$$
$$\text{Function 2: } f_2 = t$$
$$\text{Function 3: } f_3 = cos(t)$$

To test whether the system was time-invariant a simple experiment was performed on two different functions for confirmation. The procedure was to shift the input of the system and observe the output and then show that the same shift to the output of the system with a static input would create the same final output. We did this graphically using basic compositions of sinusoidal, exponential or polynomial functions. It was assumed that by being time-invariant for these three functions, disregarding any noise, that the system exhibited time-invariant behaviour.

The next step in the project was to filter the output of the black box. Two filtering techniques were employed to accomplish this. The first stage of filtering used a low pass FIR filter implemented by the `matlab` FDA tool. Different cut-off frequencies were used while discovering the experimental bode plot for the system. This allowed the Team to pass signals of different frequencies into the black box without attenuation of the desired output signal. The second stage of filtering employed a moving average filter. This attenuated the outliers of the noise that did not necessarily have a frequency value. In order to quantitatively decide whether the filter was adequate, the team defined a term called peak noise.

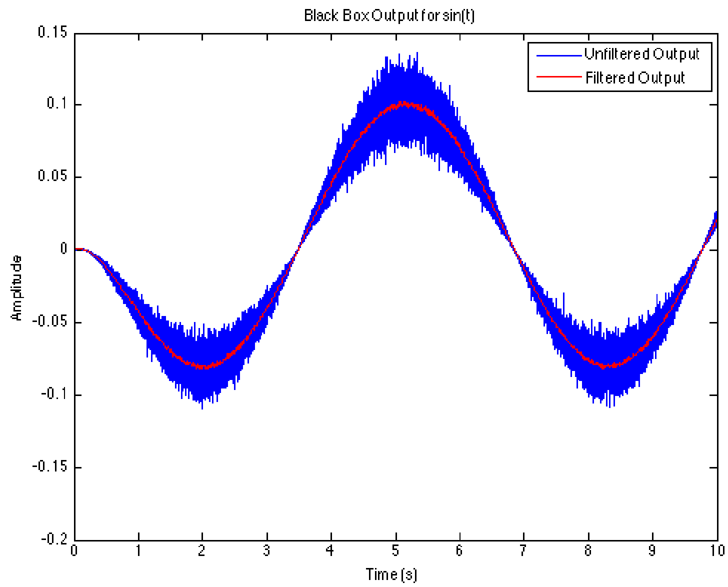

Figure 4: sin(t) Filtered vs Unfiltered

The peak noise of a signal was defined to be the height of the noise at the peak of the output signal. In Figure 4, above, it should be noted that the peak noise of the blue (unfiltered) signal is 0.065 while the peak noise of the red (filtered) signal is 0.003. Because the Team needed only the phase and magnitude information from the filtered plots to generate Bode plots, it was decided that this reduction in noise sufficed. After obtaining a controller for the black box, the filtering parameters were further tuned in order to produce the smoothest output signal. Figure 5 and 6 below summarize the values used in filtering signals at different stages of the project. When trying to find the experimental bode plot it is most important that the filtered output signal is not shifted away from the output signal without noise (actual output signal).

Low Pass Filter	Sampling frequency	Cutoff Frequency
Experimental Bode Plot	100	10
Black Box Control	1000	5

Figure 5: Low Pass Filter Data.

Moving Average Filter	Sample Size
Experimental Bode Plot	100
Black Box Control	1536

Figure 6: Moving Average Data.

Filtering for this portion of the project as described in the above tables gave rise to the most accurate tracking of the actual output signal. However, this method did not result in the smoothest signal possible. The system specifications for the given black box required that the steady state of the output be within an error band of 0.03 from 1. This was not achievable using the filtering specifications for the experimental bode plot phase of the project. A comparison of the old and new filtering of the black box can be seen below in Figure 7 and Figure 8, it is clear that control is greatly improved by tuning the filter specifically for the black box.

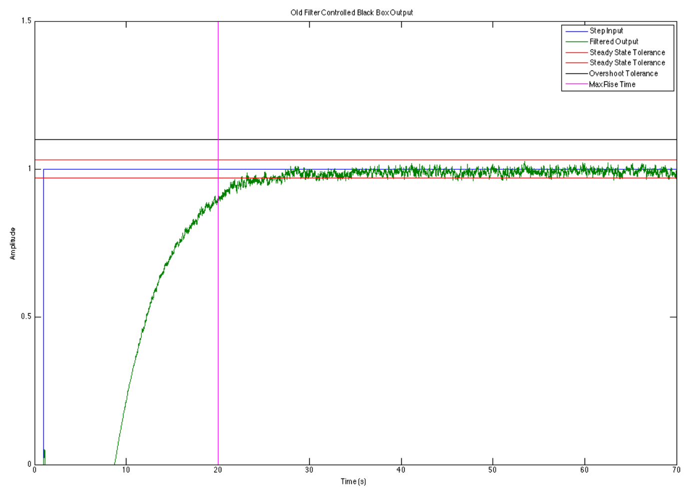

Figure 7: Control using filters from the experimental bode plot phase of the project.

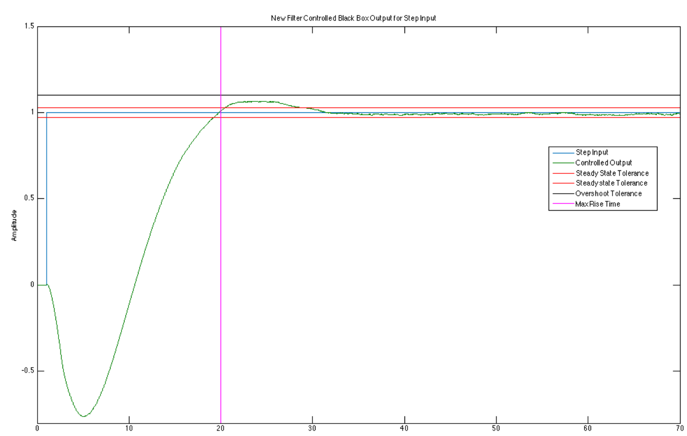

Figure 8: Control using filters tuned specifically to meet system specifications.

Because filtering for this project is purpose driven, we are justified in assuming that the filtering process for the black box is independent of the filtering process for obtaining an experimental bode plot. That is, the purpose of the first filtering process was to generate signals that could be used to accurately model the black box. The purpose of the second filtering process was to produce a controlled output of a step function that met the given systems specifications.

After the system was determined to exhibit LTI behaviour and appropriate filters were constructed, the Team began building an experimental Bode plot and transfer function. The two methods used were experimental and computational.

For the experimental part, 14 data points ranging from an angular velocity of 0.5 rad/s to 10000 rad/s were obtained using an input of sin(ωt). Magnitude gain values were obtained by comparing the max of the output signal with the amplitude of the input (being 1 for all frequencies). Likewise, for the phase analysis, the plots of the outputs and inputs were overlaid and the peak-time difference of the zeroes were compared graphically. With the data from these experiments, Bode plots were produced, as seen in Figures 9 and 10.

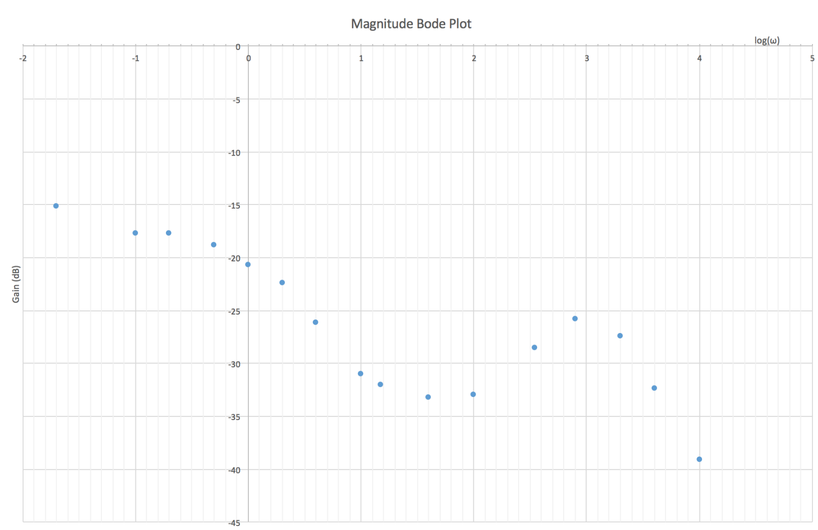

Figure 9: Scatter magnitude Bode plots for the experimental data

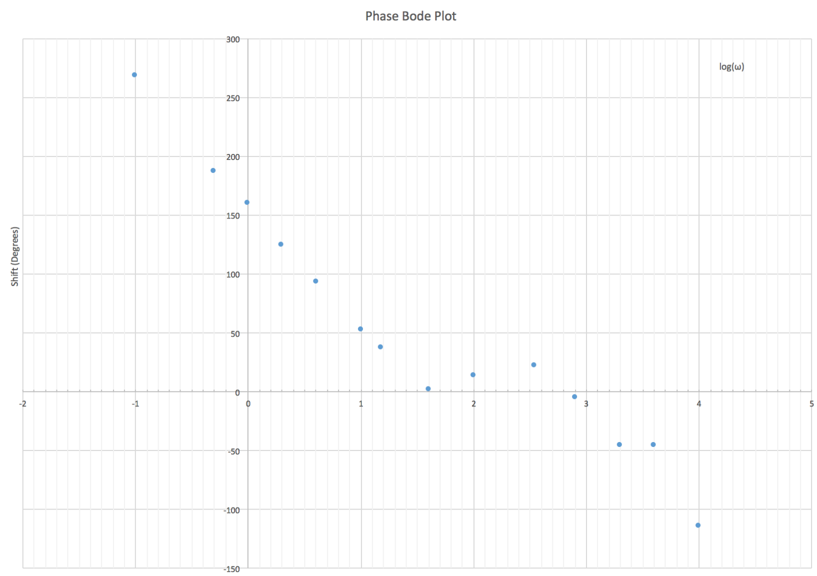

Figure 10: Scatter phase Bode plots for the experimental data

The Bode plots were printed and analyzed to determine the number of poles and zeroes of the system, as well as their locations. This was necessary to produce a computational model of the system because the `matlab` function tfest requires the number of poles of the system as an input. Furthermore, this information was required to make an estimate of the transfer function in factored form. The number of poles of the system was determined by counting the number of changes in direction of the Bode magnitude plot. That is, once a zero or pole occurs, it will contribute a positive or negative slope to the bode plot for all higher omega values in the domain. It was determined that the system had 4 poles and the bode plot continues at a slope of -20 dB/dec at very high frequencies, indicating one less zero than the number of poles. Therefore, the system has 4 poles and 3 zeroes. Figure 11 shows this procedure.

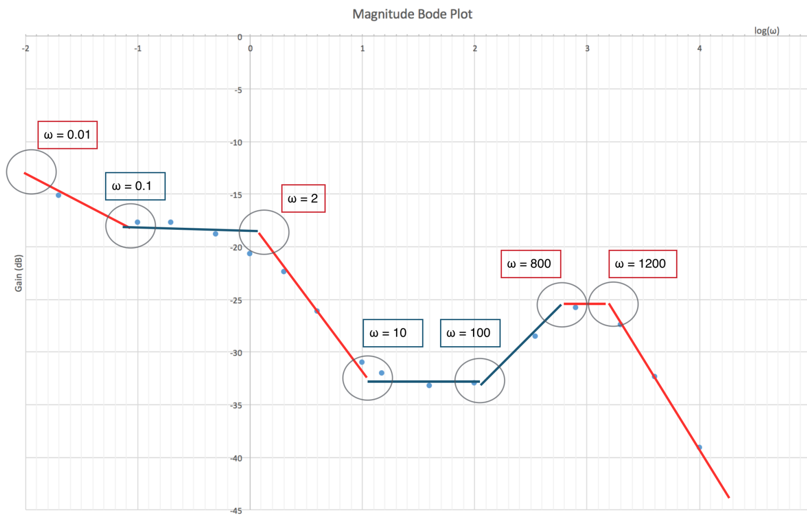

Figure 11: An illustration of the analysis of the experimental Bode plot for determining the locations of poles and zeroes

Knowing the number of the poles of the system, the process of generating a transfer function using `tfest` could begin. An exponential chirp that encompassed a wide range of frequencies from roughly 10^{-2} to 10^5 Hz was inputted into the black box and its filtered output was saved. The input, output, and number of poles were then passed to `tfest` which generated a transfer function with about 87% confidence. The accompanying Bode plots for magnitude and phase both mirrored experimental results but y-axis positions were both stretched and translated for a given frequency in both magnitude and phase. A test to compare the step response of this transfer function and that of the black box confirmed that this `tfest` generated transfer function should solely serve as confirmation alongside a transfer function generated via the experimental Bode plots. That is, the outputted transfer function did not accurately model the black box. This failure was attributed largely to a misunderstanding of the documentation of the `tfest` function as well as the low-pass filter interacting with the chirp poorly at high frequencies. Bode plots generated from the transfer function output of `tfest` can be seen in Figure 12.

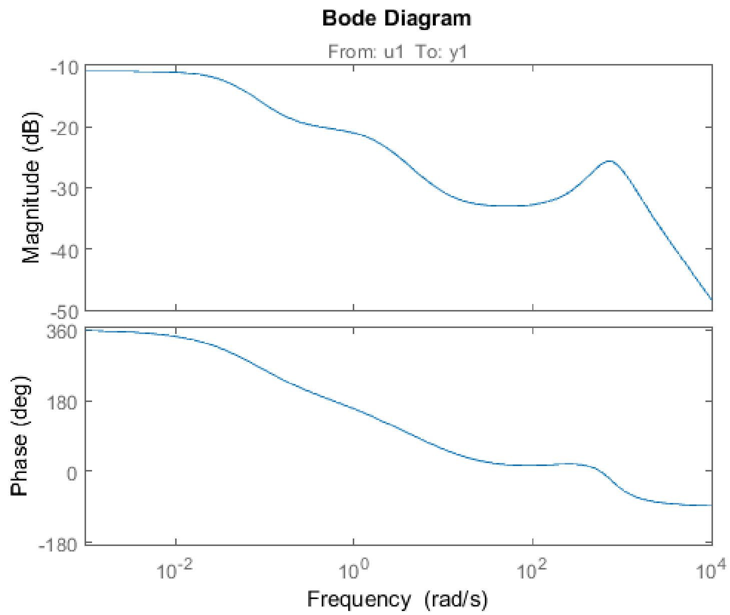

Figure 12: Bode plots corresponding to the output of tfest

An estimate for the transfer function of the system was generated by graphically observing the locations of poles and zeroes and simply constructing the function in its factored form. Given the sparse set of data points and the black boxs irregular behaviour at low and high frequencies, this was not a trivial task. Rough estimates were made for the absolute locations of poles and zeroes by drawing straight lines over appropriate portions of the Bode plot, but further inaccuracy arose from reading off of a log-scale x-axis. These large tolerances for the exact locations are shown (not to scale) by the circles in Figure 11.

With an estimate of the magnitudes of pole and zero locations, the phase Bode plot was examined to determine in which half-plane the poles and zeroes were placed. Starting at low frequencies and moving outward, conscious of pole and zero locations, the signs of the poles and zeroes were determined given the sign and angle of the phase Bode at a given location.

Now, having a first draft of the transfer function, its Bode was constructed and compared with the experimental. A number of differences in both magnitude and phase were seen. Examining the magnitude plot, the transfer function Bode plot was compared with the experimental by first studying differences at low frequencies. Adjustments to the poles and zeroes within certain tolerances created by the errors above were made. Slowly, the process continued moving outward to larger frequencies until the transfer function magnitude plot more closely resembled the experimental plot.

Likewise, the phase plot of the transfer function Bode did not fully look like that of the experimental data. A similar process was undertaken to modify zero and pole signs until the plots looked similar. The Bode plot of the final transfer function are shown in Figure 13. During both of the processes to refine and tune pole and zero locations, the overall gain of the system, K, was changed throughout to provide the best fit. This method was largely based on intuition which lead to the procedure being very slow. The final transfer function can be found in the Results section.

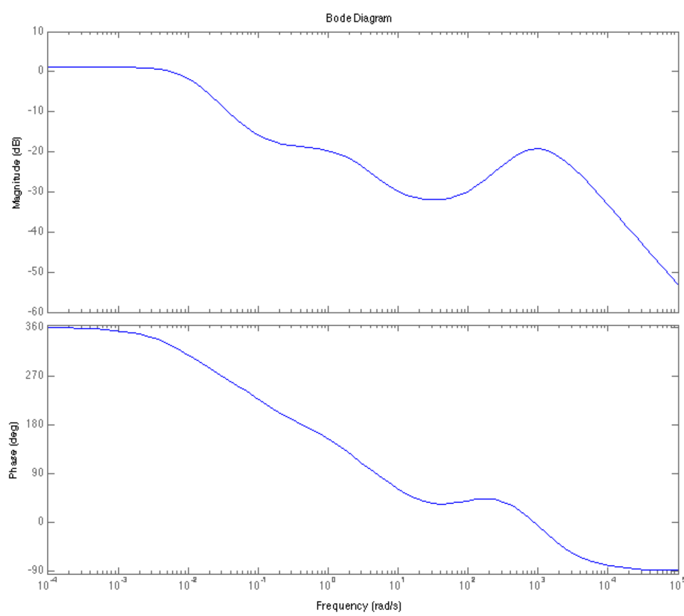

Figure 13: Bode plots corresponding to the transfer function estimate of the black box.

2.2 Control Design

The transfer function acquired experimentally led to the realization that the given system likely was, or exhibited, non-minimum phase behavior. This was a result of having poles in the right-hand plane, specifically at s = 0.1 and s = 1.

In order to control the black box, it was first necessary to develop a controller for transfer function that would either be robust enough to use further or would require minor tuning for the black box. The flowchart in Figure 14 shows this process.

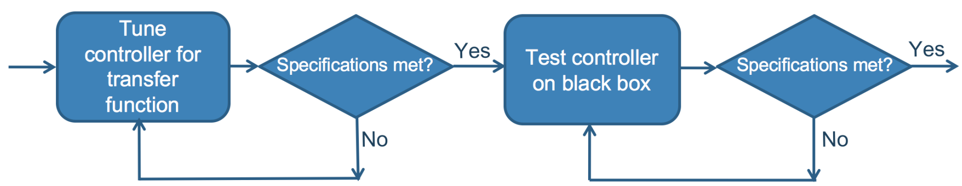

Figure 14: Decision chart showing the control design process.

Given the Team's current knowledge, proportional-integral-derivative (PID) control was an obvious choice for controlling the given system. Initial tests showed that the system exhibited significant non-minimum phase behaviour in response to a step input. That is, for a unit step, the system had an undershoot of about 0.1 for 7 seconds.

This behaviour indicated that PID control may not be capable of achieving performance specifications. This is because the non-minimum phase behavior causes a spike in the output at the transition point of the step, resulting in a reaction from the derivative component that tries to track the spike as good data, when in actuality the spike is a result of this non-minimum phase behavior [1]. Regardless, PID control was pursued to develop a base controller. After some initial configuration for the controlling constants, it was deemed that the best performance could be achieved with a derivative component of 0, i.e, eliminating the derivative component.

Having only two controller parameters to adjust, it became evident that we could employ an intuitive gradient descent procedure to achieve the best results. The procedure was as follows:

1. Guess values for K_I and K_P

2. If unstable response, go back to 1
3. Hold one parameter constant and perturb the other equal amount in both directions
4. Move in the direction of better performance (sum of rise time and settling time)
a) Movement should be large for a large change (derivative) in the performance
b) Small derivatives indicate that a valley of strong performance is being reached and thus small perturbations are most appropriate.
5. Make next movement in other direction, that is, changing the other parameter (returning to step 3)
6. Stop process once both directions for both parameters yield poor performance. A local minimum has been reached

Below are simplified diagrams showing the process.

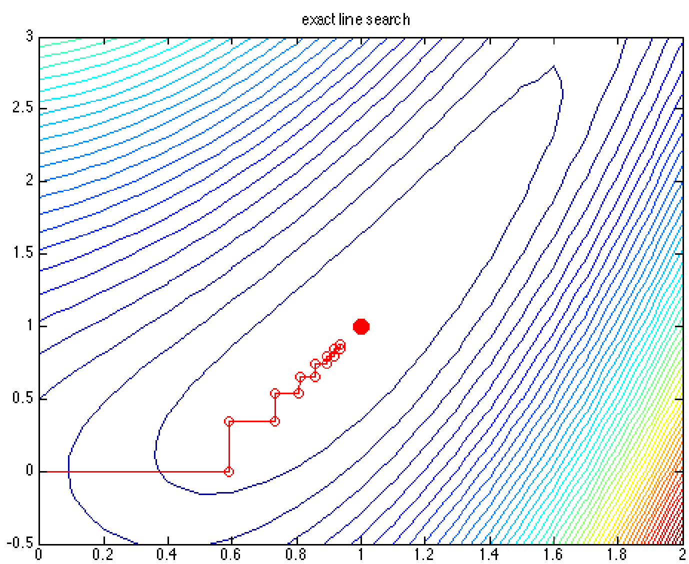

Figure 15: A diagram showing the descent to a local minimum by alternating changes in two parameters.

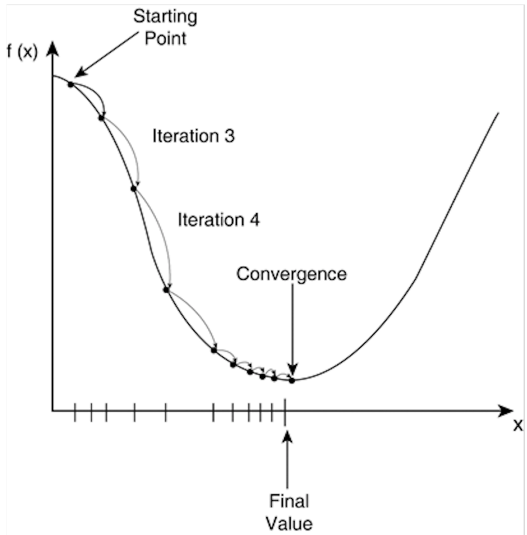

Figure 16: A diagram showing the relationship between derivative and step size when holding one parameter fixed.

After finding values of 0.0535 for the K_I and 5.28 for the K_P to be optimal in controlling the system (in a local sense), their performance could be compared with the benchmarks. For these trials, the moving average filter used 120 samples. Including artificial Gaussian noise, rise time, settling time, steady state error and overshoot were all within the performance specifications. At this point, a closed-loop control system was implemented around the black box as the plant. Figure 17 illustrates the `simulink` model used.

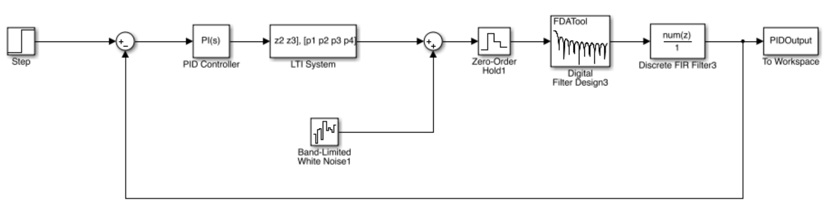

Figure 17: The `simulink` model to realistically model a closed-loop control setup for the transfer function.

The optimal values used for the transfer function were the starting point for controlling the black box. In a truly robust system, the same parameters would be effective in controlling both plants. The values for K_I and K_P were not able to reach ideal performance the black box, specifically, the rise time was not optimal. As a result, the K_P value was increased until the system rose faster than 20s - the benchmark rise time. Values of 0.0549 for K_I and 5.98 for K_P were the optimal parameters for the the black box controller. Figure 18 shows the `simulink` model for controlling the black box.

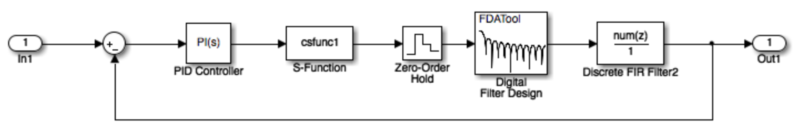

Figure 18: The `simulink` model for controlling the black box.

It was recognized that the non-minimum phase behaviour was a large burden on the control of the system and greatly affected the systems ability to rise fast enough while settling in an appropriate fashion. Furthermore, it impaired the ability to produce a robust controller that satisfied the specification for each plant - a goal of the project. New methods needed to be researched to improve this. Zero-pole cancellation [2] and zero-pole compensators [3] were researched and attempted, but implementation resulted in either instability or other unsatisfactory results such as a lack of steady state. In the interest of time, coupled with the fact that the bottom line of reaching the performance benchmark had been met these endeavours had to be dropped. Further discussion is included in the Future Work section.

Further justification for not utilizing zero-pole cancellation was made when the nature of the black box was analyzed as well as when the real-world application of temperature control was considered. Disturbance, noise, and the exact locations of the zeros and poles of the black box made the process of canceling zeroes very sensitive. Introducing a RHP pole to cancel a RHP zero will potentially cause the system to no longer be IBIBO stable if the cancellation is not perfect. There is a high probability of this given noise and potential disturbances in the control loop; making it a non-robust solution. In fact, having a zero and pole very close to each in the RHP can actually exacerbate the unstable effects [4].

2.3 Results

After the process of determining the ideal locations of the poles, zeroes, and gain of the system, the transfer function below was obtained.

$$\frac{220(s-0.1)(s-10)(s+100)}{(s+0.01)(s+2)(s+800)(s+1200)}$$

A controller was then designed for this transfer function so that the output of the system fell within specifications of the black box. In 19 notice that the output of the controlled experimental system meets the design criteria.

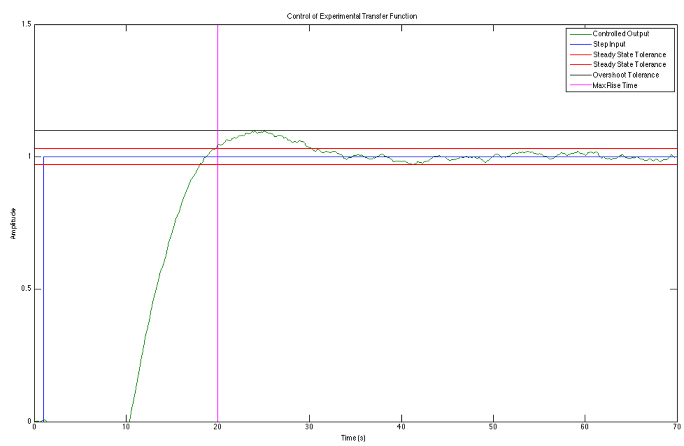

Figure 19: Control of the experimental transfer function.

This controller provided a starting point for the controller for the black box. After applying this controller to the black box it was found that although it worked, it did not meet system specifications. Further tuning of the controller and filter parameters produced the result seen in 8 where it is clear that the output meets all of the system specifications. 20 shows that the controlled output of the black box remains stable for extended periods of time, thus confirming the control method employed for the system.

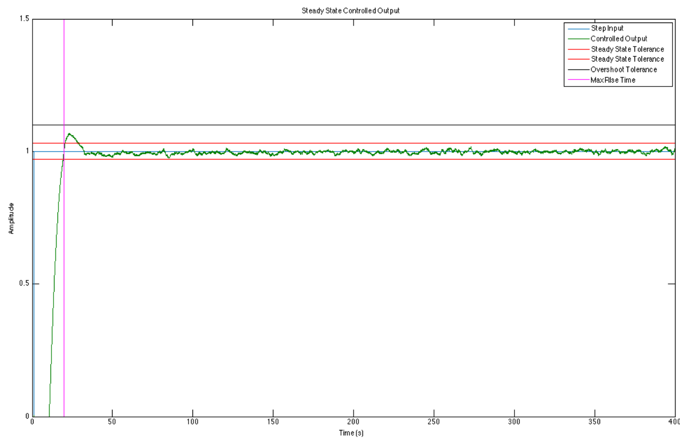

Figure 20: Steady state control of the black box.

2.4 Technical Assumptions

There were a number of assumption made throughout the technical part of the assignment to develop a model and a controller for the black box. These assumptions are discussed in chronological order below.

LTI Determination: The primary assumption made when determining whether the system was linear and time-invariant was that the system did not need to fully satisfy these conditions but rather exhibit these behaviours. This is coupled with the fact that the determination was made from examining only a sample of functions; primarily sinusoids. Furthermore, LTI behaviour was necessary for the proceeding analysis as further models relied on this assumption. That is, in reverse engineering the system, the LTI determination did not have to be exactly precise.

Filtering: The main assumption made with the filtering process was that any filtering used did not affect the output characteristics. This was reasonable in the determination of experimental Bode plots because locating poles and zeroes already has more significant sources of error (such as the exact location of inflection and roll-offs), so that small differences in gain or phase difference attributed to filtering would not be significant.

Bode/Transfer Function Development: A number of assumption needed to be made during the Bode process and during the determination of an accurate transfer function. The first assumption made was that there were a reasonable number of poles are zeroes. This was an important assumption because a pole and zero could be very close in magnitude and therefore be very difficult to see on a magnitude Bode plot. This assumption is very specific to this project and shows that the method used is not robust. Using tfest or some other automated process eliminates the need for this assumption. Furthermore, the locations of the poles and zeroes were assumed to be within the range of 10^{-2} to 10^{4} Hz. This assumption was made via guidance from supervisors, but could have been tested by passing a large range of frequencies via a chirp through the black box and observing the corresponding Bode plots. This would be difficult with the noise of the system and the potential conflict with the low-pass filter. Furthermore, the zeroes of the system were refined by comparing the step-response of the potential transfer function with that of the black box. This process was only possible because of the reverse-engineering nature of the project.

Controlling the black box: One major assumption made while controlling the black box was that controller specifications, K_I and K_P, would be tuned and refined for a system that has no disturbances. This is not robust and would not be viable in our application of controlling temperature in a house. A more complicated controller, potentially utilizing feed-forward control loops, would have to be implemented in this case.

3 Application to Thermostat Control

This control design was applied to the smart thermostat. This is a programmable thermostat that has the ability to store information from a variety of inputs, and adapt autonomously to trends in the user's lifestyle. The control design for these devices directly parallels the process that was followed when controlling the black box. A closed loop control schematic is shown in Figure 21.

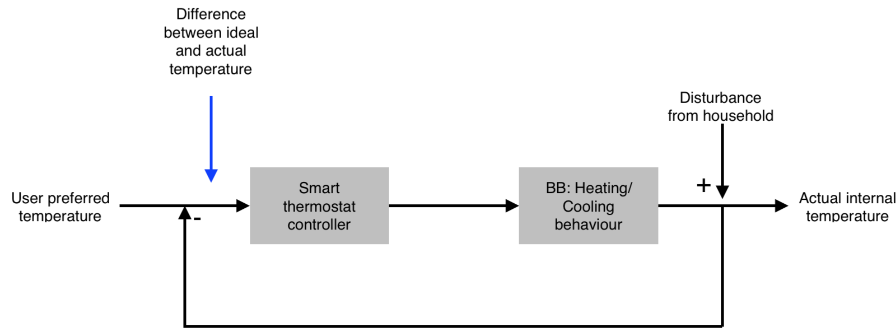

Figure 21: Closed-loop control schematic for a smart thermostat.

3.1 Input

The initial input to this system is the desired temperature. For a typical thermostat, this would be directly set by the user. However, in the case of the smart thermostat, this input can be determined by the software recognizing trends in collected data. With a balance of autonomous input selection, and manual override capabilities, the user can rely on optimal comfort, with lower energy bills and environmental impact.

3.2 Disturbance and Control Input

It is also a necessity that this be a closed loop system. Without a reading of the current ambient temperature, the control could not adjust for the effect of disturbances, such as doors and windows opening, the stove being in use, or any other day to day activities that slightly alter the temperature of a house. With the closed loop, the difference between reference and measured temperature (error) is then fed to the controller. The disturbance enters the system in the feedback. This is because the factors that provide disturbance are changing what the sensor would measure as the temperature of the house, which skews the error. This disturbance must then be accounted for, and assessed by the controller.

3.3 Control Output

Assessment of disturbance employs a delay model. This means that any positive or negative spikes are not accommodated until they either surpass a threshold temperature difference, or they remain active for longer than a given threshold time period. By not trying to adjust for disturbances that are short-lived or small in magnitude, the furnace is not required to constantly turn on and off. Reducing this will relieve stress on the mechanism of a furnace, such as the ignition and valves. If the error is significant, the controller must then provide an input to the furnace. For a natural gas forced air system, this input is in the form of power to the fans, and rate of gas release. The controller will provide this signal based on collected data from previous patterns, or manual tuning from the user. Different signals will change the rate at which the furnace heats the home, the amount of overshoot there will be, and the settling time. All of these factors affect the comfort of the user and energy efficiency, which in turn will affect one's heating bill.

3.4 Unknown Transfer Function

In the technical component of the control design process, the black box accepts an input signal from the control, and produces an output for which the behaviour is unknown. The analog for the black box in a home thermostat application is that a known amount of thermostat control inputted into the furnace, will change the internal temperature with varying behaviour. That is, the transfer function between inputted control and resulting temperature is unknown. This unknown transfer function depends on the geometry and construction of the building. This is due to the pattern of heat dispersion through rooms of the home, and insulation or lack there-of. As warm air propagates through the house, the sensor will be subject to a varying temperature reading, and the quality of insulation will determine the effect of external temperature. The feedback aspect of the control system will therefore be constantly adjusting the black box input. Keeping in mind that these thermodynamic properties would vary with the current ambient temperature of the home, it is clear that it would be near impossible to develop a precise model for such a system.

3.5 Control Influence by Stakeholders

Each performance indicator for the control system has a distinct parallel in the thermostat application. These are seen in Figure 22.

Stakeholder	Bias
User with economic priorities	Desires slower rise time and smaller overshoot to conserve energy and reduce cost.
User with comfort priorities	Desires shorter rise time for comfort sooner.
Government	Slower rise time for less energy consumption and more money in hands of citizens.
Regulators	Slower rise time and smaller overshoot, as it reduces environmental impact and lowers utility bills (i.e. when considering a landlord-tenant agreement).
Nest and Investors	Bias for product that serves customers needs well, whatever they may be. This way customer satisfaction and sales will rise.

Figure 22: Control parameters and their temperature control analog.

There are several significant trade-offs associated with varying the measures above.

- An increase in rise time sacrifices energy and money for faster comfort.
- A decrease in overshoot sacrifices faster comfort for energy savings.

These trade-offs allow for the tuning of K_P and K_I parameters to satisfy different stakeholders. The biased needs of each stakeholder are seen in Figure 23.

Parameter	Thermostat Control Analog
Rise Time	Time it takes until temperature reaches, but not necessarily stays at, the desired temperature.
Overshoot	Amount by which the temperature rises past the desired temperature.
Steady-state Error	A tightly defined temperature range. Thought of as the region of comfort. From experience, this is often around 0.5 degrees Celsius.
Settling Time	Time taken until the system settles and remains within the steady state error.

Figure 23: Control parameters and their temperature control analog.

Nest should investigate which stakeholders it would want to give control over these parameters. It is likely in Nests best interest to boost customer satisfaction by giving customers control of the parameters. Users could then adjust their systems responses based on the scenario. A person who has guests coming over soon would want to spend more energy to quickly raise the temperature of the home, whereas someone on a long commute home from work would prefer a cheaper, longer rise time as long as the home is at their desired temperature by the time they arrive.

3.6 Assumptions and Limitations of Application

- It is assumed that furnaces and air conditioners are not binary and that they can operate anywhere within a range of power settings. This may not be the case with certain heating set ups like baseboard heaters.
- It is assumed that a furnaces efficiency decreases with a rising power setting. That is, it takes more energy to heat a home quickly than to heat a home slowly. A similar argument holds for air conditioning.
- This thermostat control case study makes the assumption that in a single day both the air conditioning and furnace are used to control ambient temperature. In practice however, this rarely occurs. In the winter the furnace is used to raise the temperature, but there is no control system that lowers the temperature. Instead the cooling mechanism is the heat of the home leaving by convection to the cooler outdoors. This mechanism is external to the control system, and its effectiveness is based on the imperfections of the homes insulation. This assumption would affect the performance of the control system, which would result in slower cooling times in the winter. There is a parallel effect for the summer. As a next step, Nest could incorporate controllable windows or vents into its systems so that it could also have control over cooling in the winter and heating in the summer.

3.7 PID versus Bang-Bang Control

The motivation for this project was to improve upon older control methods for thermostat control by integrating PID control. It is common for older heating systems to operate using a bang-bang controller, whose poor performance is seen in Figure 24 Such controllers operate in a binary state of either on or off. This means rise time is limited by the mechanics of the furnace, and when holding a steady temperature, the controller continually switches between on and off as external factors disturb the output. Disadvantages of the system include fixed rise time, inability to hold a steady state with a high degree of accuracy, and wasted energy spent on the fluctuations. This results in larger utility bills and less comfort in the home.

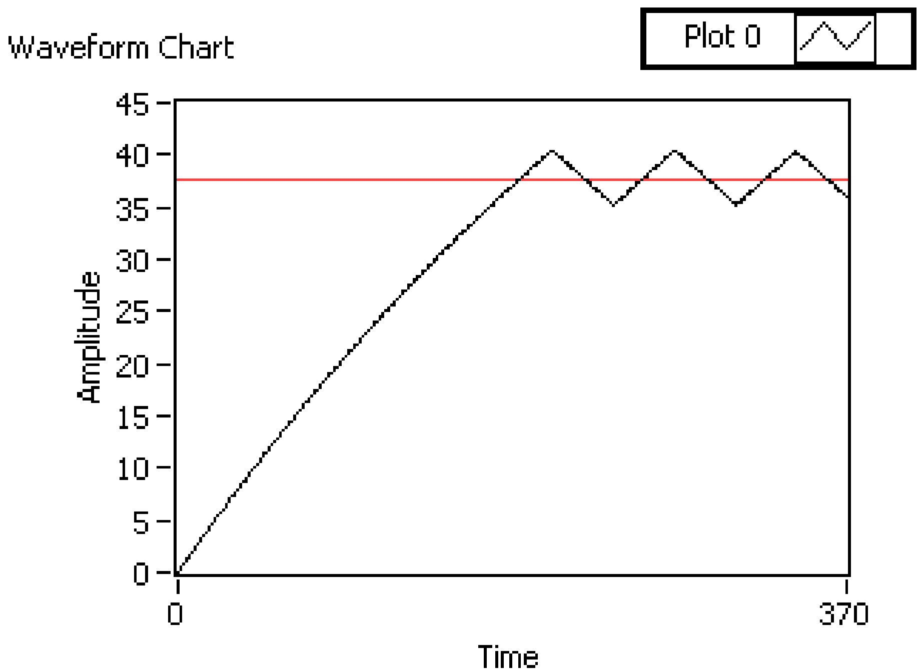

Figure 24: A binary controller oscillating around a set output.

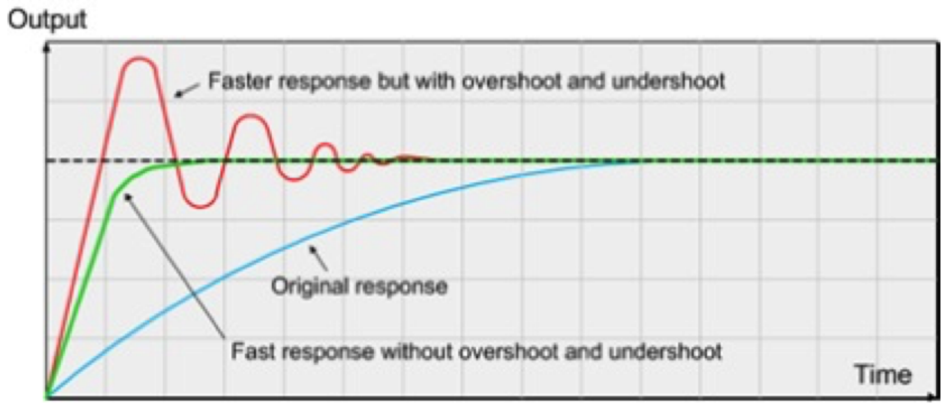

Figure 25: Three varying responses, with the red line indicating faster heating time and blue line representing slower line.

A proportional-integral-derivative (PID) controller offers several advantages. Its use of current, past, and future error allows it to access a range of inputs, allowing it to use a maximum rise in temperature, with minimal overshoot and oscillation at steady state. This permits a higher level of comfort within the home with a lower electricity bill. Furthermore, because each component of PID control has a tunable parameter, individual users can select a balance between comfort and efficiency. Difference responses are seen in Figure 25.

3.8 Non-Minimum Phase Behaviour

The response of a forced air durance will exhibit non-minimum phase (NMP) behaviour. Figure 26 simply displays the workings of a furnace. The NMP behaviour is a result of the air flow and the exhaust component. The furnace operates with two intake vents, both drawing interior air. The first is labeled Combustion Air, and this is pumped through the exhaust vent, and pumped out of the house. The second feeds air to the House Air Blower, and is pumped through the secondary heat exchanger, and back into the house. Both of these fans start up at the same time, which means that, at time zero, there must be an equal amount of exterior air entering the house as there is pumped out of the exhaust vent. This exterior air is what will cause the NMP behaviour. As this air enters the home, it will naturally be pulling the ambient temperature in the negative direction. The air that is being circulated through the secondary heat exchanger heats as it flows over the exchanger. It will therefore be subject to a delay determined by the rate at which the exhaust gases can heat the exchanger. Therefore, initially, the ambient temperature will actually experience a decrease.

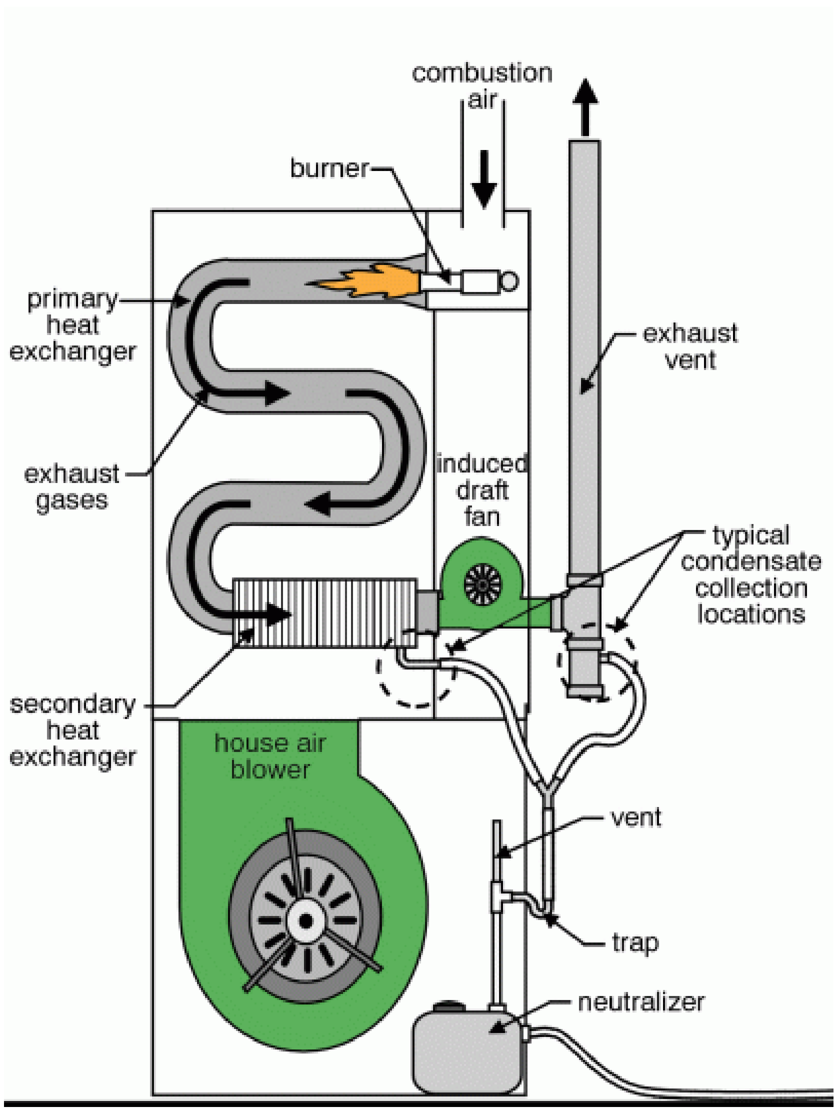

Figure 26: Forced Air Furnace Diagram [22]

4 Triple-Bottom-Line & Additional Considerations

4.1 Stakeholders

The development of more sophisticated control methods in smart thermostats will affect a spectrum of parties. Below in Figure 27 is a Venn diagram illustrating the main stakeholders and how they interact with and are affected by the triple bottom line of smart thermostats. The determination of the importance for each stakeholder was a combination of how much triple bottom line extension these parties have (i.e their Venn diagram overlap) as well as the size and importance of these groups. As a result, the largest groups, user and the government, who also have the largest interaction with the triple bottom line are the most important stakeholders. Justification for stakeholder interactions with the triple bottom line are discussed in Section 4.2.

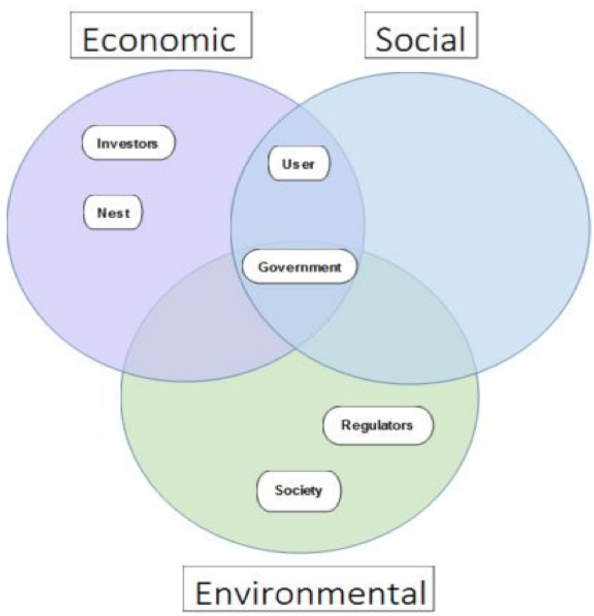

Figure 27: A Venn diagram illustrating how stakeholders interact with the triple bottom line.

The above illustrates that governing bodies and the thermostat users interact most heavily with the tripe bottom line. Governments interact economically though incentives and rebates, which also promote environmentally friendly behaviours of their citizens. Furthermore, the ability for certain citizens to allocate saved income from using a smart thermostat to other aspects will improve health and wellness of the population. For consumers, their TBL interaction is focused in economical and social. The reasoning for this is the same as for the government, except not all consumers care about the environmental concerns [5].

The secondary stakeholders are investors, the smart thermostat company, society as a whole, and regulators. Investors and the company are primarily concerned with profits associated with the sales, whereas regulators and society are most concerned with carbon emissions and reaching sustainable goals. Regulators are listed separately than the government because the two may have separate mandates and not always operate in lockstep with each other.

4.2 Economic, Environmental, & Social Impact

4.2.1 Environmental

Programmable thermostat control has a significant environmental effects.

Initially, some energy utilities in Ontario will offer customers a programmable thermostat for free up front, with built in controllability for the company [12]. This allows the company to briefly reduce consumption during peak times. This reduction typically relieves the strain on the system by an average of 1 kilowatt per home. Since 56% of Ontario households have a programmable thermostat [14], this slight reduction could reduce the total consumption by nearly 3 million kilowatts, which represents over 12% of the average peak demand in a day [8]

From the side of the homeowner, there have been studies conducted to demonstrate the savings that a well programmed thermostat can have. Using a daytime winter temperature of 22 degrees Celsius as a benchmark, two different programs were compared. The first set the constant daytime temperature, and reduced it to 18 degrees at night time. This program resulted in a 6.5% savings in natural gas and 0.8% savings in electricity. The second program was more closely related to a programmable thermostat. This program again used the benchmark daytime temperature, but reduced the temperature to 16 degrees while the home was unoccupied or at night. This more adaptable system resulted in a 13% savings in natural gas, and a 2.3% savings in electricity [13]. We can now combine this study with household the 2014 records from Statistics Canada. In Ontario, 56% of households reported having a programmable thermostat. Only 83% of these, however, have actually managed to complete the programming. This gives us 46% of Ontario households use a programmable thermostat to its full potential. Figure 29 combines the energy savings study, with Ontario household statistics to determine the total savings in Ontario as a result of programmable thermostats. Program 1 and 2 both compare to a society that does not manage the temperature (and it remains at 22 degrees). Program 1 assumes that the 46% of people reduce the heat to 18 degrees at night time, while Program 2 assumes that the %46 program the thermostat efficiently. Figure 28 illustrates the necessary statistics used for these calculations. These statistics were all taken from the 2014 census, provided by Statistics Canada [14].

Households	
Ontario	4887510
Using Programmable thermostat	2737006
Programming the thermostat	2271715
Using Electric heating	684251.4
Using Natural Gas Heating	3714508

Figure 28: Housing Numbers used to calculate savings

	Program 1			Program 2		
Household Heating Method	Savings per Household (%/100)	Savings per Household (TJ)	Total Savings (TJ)	Savings per Household (%/100)	Savings per Household (TJ)	Total Savings (TJ)
Electricity	0.008	0.000812	555.745	0.023	0.002351	1608.909
Natural Gas	0.065	0.002766	10275.63	0.13	0.005709	21204.83
Total			10831.38			22813.74

Figure 29: Total Savings in Ontario by using manual or programmable thermostat

From Figure 29, it is clear that the environmental benefits to a programmable thermostat are significant. By simply reducing your thermostat to 18 degrees overnight, Ontario as a whole saves over 10 thousand terajoules per year. However, when using a programmable thermostat that reduces temperatures throughout the day when heat is not needed in the home, the savings increase to nearly 23 terajoules per year. This number represents 4.2% of Ontario's total consumption [14].

An interesting remark from these statistics is the difference between citizens with a programmable thermostat, and those that have actually managed to program it. There are 465291 households in Ontario that own a programmable thermostat, but are not exploiting the advantages. This could be attributed to a few different issues, but changing technology is the primary obstacle for users. The Nest thermostat will help this greatly with its user-friendly interface, mobile capabilities, and its cognitive ability to accept data and adapt autonomously. Currently only 83% of citizens with a programmable thermostat are using it to its full potential. It is clear from the tables above that programming your thermostat correctly can have a huge impact on our environmental footprint; so it is imperative that they are not only present in peoples homes, but that the homeowner is educated and able to program the device.

4.2.2 Social

More efficient and well-controlled temperature controls bring many societal benefits with them. From the economic analysis that follows below, the average household would save $170 annually on utilities by installing nest. Low and middle income homes are forced to choose between energy and food. In the United Kingdom, every winter over 750,000 seniors choose between paying for heating or food [24]. Malnutrition can have social costs that include poor school and workplace performance that perpetuate a cycle of poverty [23]. By reducing average household energy costs by $170 annually, Nest will free up budget space so that low income households are not forced to make precarious decisions with high health and social consequences.

Proper air temperature affects peoples psyche and productivity. Research shows that an office thermostat set at a cool temperature of 68 degrees F increased human errors by 44% [16]. Additionally, experiencing cold temperatures can damage relationships as it causes people to perceive others as less generous and less caring [16]. Better temperature control will reduce the magnitude and time of the error between actual and desired temperature, which will in turn improve productivity and interpersonal relationships.

Lastly, better temperature leads to more comfort and relaxation around the home. It affects daily decisions from what we wear to what we eat [17]. Having better control over ones temperature environment, and better yet, delegating this control to learning algorithms embedded in Nest, adds predictability to ones life and allows one to focus on larger decisions instead of sweating the details.

4.2.3 Economic

There are a number of financial implications for the use of smart thermostats. Lowering energy bills by reducing consumption are the main sources of saving that can be attributed to installing a smart thermostat. The other significant factors are any tax-cuts, credits or other legislation that financially rewards responsible energy practices.

In a report published by Nest which encompasses two third-party independently funded studies and one Nest-funded study found that installing a Nest system could result in $131 to $145 USD a year saving by reducing heating usage by 10-12% and cooling usage by 15%. There are many variables in studying smart thermostat usage such as occupancy patterns, weather, and home equipment. As a result, the data was taken from a large sample (1359 homes across the US), averaged and fit to a linear regression[6].

With a purchase price of $250 USD, the investment in a Nest Smart Thermostat will pay for itself partway through its second year and have an estimated 10-year net present value (NPV) of about $1,200 [9].

A number of rebates and incentives are offered through local utility and energy companies to promote the use of smart thermostats. For example, Nest has a partnership with Hydro One that offers credits of $125 when a user participates in Nests Rush Hour Rewards Program. This program takes advantage of the automatic capabilities of Nest to turn on the home air conditioner ahead of summer rush hours for cooling the house. This incentive is offered to avoid throttling energy use at peak times and ideally has little effect on the Nest user [10]. Ontarios SaveONEnergy offers up to $400 incentives for using Energy Star cooling products. Programmable thermostats lost their Energy Star rating in 2009 in some jurisdictions due to the findings that most people were not properly programming their systems [6]. On the other hand, incentives of $180 are still being offered for using programmable or smart thermostats in some places [11].

4.2.4 Economic Analysis

At a savings of $174 CAD ($131 USD) per household, this could result in a nationwide savings of $2,317,787,010, obtained by multiplying the per household savings by the most recent figure of the number of households in Canada [7]. This number represents how consumers in Canada could re-direct their spending to other parts of the economy. Some of these redirected funds will necessarily go towards productive outlets such as education, health, and other industries.

4.3 Regulatory concerns

The regulatory concerns associated with the control of a programmable thermostat system relate to the social aspect of the triple bottom line. Accessibility, degree of programmability, and the responsibility of living standards are the three main areas affected by regulatory matters. The Ontario Building Code Act of 1992 states that all thermostats must be placed in a barrier-free path of travel, and be accessible to a person in a wheelchair using a side approach. The thermostat must also be placed 1.2m above the finished floor [18]. The feedback reading of the sensor depends heavily on the location of the device, so these restrictions affect the response of the control system. The Americans with a Disabilities Act (ADA) introduced the standard that the operations of a thermostat cannot require a rotation of the wrist and all functions must be operable using a closed fist with a force no greater than 22.2N [19]. Once programmable thermostats became popular, the California Building Energy Efficiency Standards required that a thermostat must have the capability to handle four separate programmable time periods [20]. When considering the regulations regarding temperature and standard living conditions, multiple social issues are considered. The Ontario Landlord-Tenant agreement handles the complicate matter of responsibility for heating a living area. When a landlord decides to include heating in the rental cost, they are responsible to keep every habitable area at 20 degrees Celsius. This measurement is taken 1.5m off the floor, and 1m away from any external wall. This, however, does not apply if the tenant can control the temperature with a central heating unit. If the cost of heating is not included in the rent, then the problem arises of damaged or plumbing as a result of a lack of heating.

The responsibility to pay to have this fixed belongs to the landlord, unless there is proof of negligence or deliberate actions by the tenant that lead to the damage (ie. Leaving a door or window open, or shutting off the heat completely) [21]. The control of the programmable thermostat system is a key component of any landlord-tenant heating dispute, because the output of the system is the direct topic of debate in this case.

Once these regulatory concerns are considered, the team could see that there are real world implications of the results of our control system. In the situation where the thermal conditions of a dwelling are under legal scrutiny, the tuning of control parameters will be brought into consideration. If a tenant is developing a case against a landlord that the house is not being held to the standard temperatures, there will need to be concrete evidence that these claims are not simply a result of low control inputs which would result in a slow rise time, but an acceptable end result. To implement a final solution for this application, we would have to consider the requirements of all relevant stakeholders, and how they are affected by these regulations. This balance would need to meet specifications based on the need for "acceptable living standards" as laid out in the Landlord-Tenant Act. However, it would also need to consider the fact that the user and the customer are not necessarily one and the same. This will add the need for an energy and cost efficient solution.

5 Conclusions & Recommendations

5.1 Summary of Accomplishments

A filter was designed that decreased peak noise by a factor of 20. An experimental Bode plot was constructed using filtered outputs, and an experimental transfer function was derived from it. Next, a PI controller was tuned for the transfer function to the required specifications. This was used as a stepping stone for PI tuning, so that this PI controller could next be applied to the black box. It was then fine-tuned further to meet and exceed performance specifications.

5.2 Next Steps

There are a number of directions for further work that could be pursued. These next steps can be categorized into technical next steps as well as further extending our application correspondence. For technical next steps the primary goal would be to develop a more robust controller that further improves on the performance criteria. In order to develop such as controller, more creative and clever methods must be researched and implemented. Techniques such as pole-zero cancellation and or pole-zero compensators may be imperative in reducing the negative performance effects of non-minimum phase behaviour. In the current controller, much of the rise time and settling time is affected by the step responses initial dive. Reducing or eliminating this dive would greatly improve these metrics of performance. As discussed, these methods can have negative consequences if implemented poorly and without awareness for noise and disturbances. As a result, tried and tested methods must be used. The project can be improved in a number of ways to better extend the relationship between the application and technical aspect of the project. Developing a library of controllers for various performance characteristics fit for different stakeholders. That is, faster rise times for higher demand heating and cooling purposes would require different PI tuning. On a similar note, this controller could be extended for applications with much stricter temperature control such as mechanical or chemical systems engineering.

5.3 Recommendations

If this project was undertaken again, the technical procedure would be much different. First, knowing the importance of the experimental data earlier would have indicated the need for a large set of data points. This would provide a much faster and reliable procedure in locating poles and zeroes of the estimated transfer function. Furthermore, a hybrid experimental and `tfest` model may be the best option for developing the bode plots. This is because the chirp operates well at low frequencies, but conflict with the filters at high frequencies. As a result, `tfest` could develop the Bode plot for low frequencies and experimental data could be used for higher frequency points. Furthermore, a better understanding of the parameters in a PID controller would be greatly beneficial in tuning the controller. The intuitive gradient descent approach was effective but locating an initial point that produced a steady state was difficult process that involved random guessing.

6 Appendix

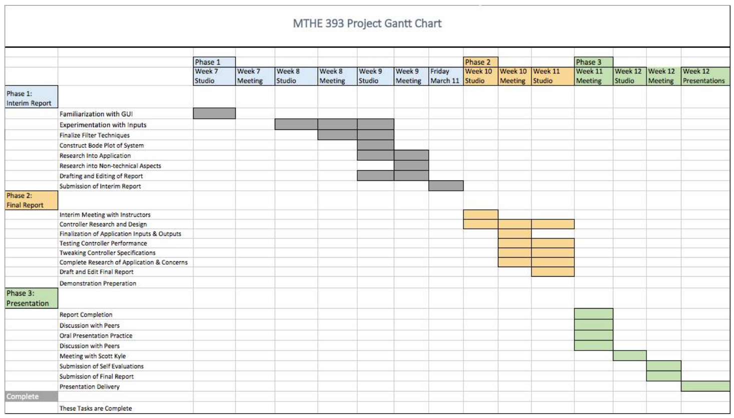

Figure 30: Gantt Chart for Remaining Weeks.

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