NEURAL NETWORK DETERMINED THERMAL REGULATION OF SYSTEMS WITH REMOTE INPUTS

By

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CHAPTER 1

Introduction

Human thermoregulation models, where metabolic rate is used to maintain thermal homeostasis, have been of interest to the Nation Aeronautics and Space Administration and the United States Army to anticipate human physiological changes in extreme temperatures. Both the astronaut and solider are often asked to perform in inhospitable environments, and design engineers need to know how the body will react in these exposures. These same type of models have also been used to design better heating, ventilation, and air conditioning (HVAC) systems for buildings or cars by predicting what humans will feel under various conditioning scenarios Katić and Rongling Li (2016). We think human body thermal models could find a third application in the medical field.

Existing thermal models, however, have limitations in health diagnostics due to the reliance on averages that are used to model the response of a canonical person. Under identical thermal environments, any two people will respond differently because of differences in body composition, vasculature, acclimatization, and so forth. The space and defense industries are interested not in how an individual will respond but how a typical person will respond. Consequently, the human body thermal models are designed to mimic an average human being. This approach is not conducive to personalized medicine or to understanding how a specific individual will respond to a particular therapy. An additional concern is how the models are calculated. Currently human thermal models rely on heuristic control of thermoregulatory physiological processes like metabolic rate, vaso-constriction and dilation, sweating, and shivering. With the control parameters determined for a canonical version of a human body thermal model, global core and local skin temperatures are calculated for varying external thermal environments. In medical applications, the heuristics used to control a response need to be customized for an individual, yet there is no path forward to make this happen.

Replacing the heuristics with a neural network control system trained on measured data could be advantageous for these healthcare applications. By measuring an individual's response to a changing thermal environment and developing a neural network control strategy to mimic these results, we can train on an individual instead of an average (non-existent) person, which is critical for personalized medicine technologies. Goto and Goto (2017) In addition, the neural net approach is particularly appealing because neural networks were inspired by the learning, classification, and decision making abilities of the brain. Here, we are using the brain-motivated neural network to model the brain's control of the body's thermal envelope.

The challenge of using a neural net for control of the human body thermal model, however, is that we can not measure those parameters that we want the neural network to sense as input nor that will be controlled as output. The brain has access to temperature sensors throughout the body and adjusts the thermal generation mechanisms to maintain homeostasis. Yet, we are unable to train a neural network to behave the same way because we do not have access to the internal sensors that are available to the brain. Instead, we must train our neural network controller to use external temperatures, which are measurable, as an input. Moreover, we can not measure the control parameters directly either. That is, measurement of the thermal generation mechanisms such as amount of vasoconstriction, shivering, metabolic rate, etc. are inaccessible as well. If internal human body control parameters could be measured, learning and regulating the internal workings of the body would be a much more straight forward problem. And, assuming a certain behavior of the internal workings could be highly flawed in a person seeking medical care. To overcome these challenges, we must incorporate the thermal model into our neural network training process and testing process. The physical heat transfer model is what connects those parameters that we can not measure (internal control parameters) to those that we can (external temperature measurements).

A preliminary study using a one-dimensional forward conduction model instead of the human body thermal model will be performed first.

CHAPTER 2

One Dimensional Forward Conduction Model

We will use a one-dimensional forward conduction solution with volumetric generation to estimate core and surface temperatures resulting from changing environmental conditions imposed through convective boundary conditions. The generation rate is controlled with a PID controller to maintain a core temperature despite the varying boundary conditions. This simple system mimics the human body in that metabolic pathways (generation) are controlled by the brain (PID) to maintain homeostasis (constant core temperature) with varying environmental conditions (boundary convection). The foregoing model will be exercised by varying the free stream temperature through the boundary convection. The calculated external surface temperature of the one-dimensional slab will be used as training data for the artificial neural network (ANN). The ANN will be designed to produce the same response as the PID controller using variation not in the core temperature (as does the PID) but in variations in the surface temperature. The ANN controller will not be dependent on the surface temperature alone but will depend on the time rate of change in the surface temperature, so a temperature history will be provided as training data.

The process for creating the training data will be described first, then the details of the ANN and how it is coupled to the forward model will be described. Starting with material from the University of Nebraska's Green's Function Library of Nebraska Lincoln (2019) and building the forward transient conduction equation is given with generation as

$$\nabla^2\theta + \frac{q'''}{k} = \frac{1}{\alpha}\frac{\partial\theta}{\partial t}, \tag{2.1}$$

where the temperature $\theta = T - T_0$ is the temperature difference relative to the initial temperature of the system. Therefore, the initial condition $\theta(t=0) = 0$ is homogeneous, and $\alpha = k/\rho c_p$ is the thermal diffusivity of the plate. The conduction is modeled on the half-plane due to symmetry, so the boundary at the centerline ($x = 0$) is an insulated condition.

$$\left.\frac{\partial\theta}{\partial x}\right|_{x=0} = 0. \tag{2.2}$$

Heat is convected away from the plate of thickness $2L$ on the external side.

$$-k\left.\frac{\partial\theta}{\partial x}\right|_{x=L} = h[\theta(x=L) - \theta_\infty], \tag{2.3}$$

where θ_∞ will be varied to create training data. The solution is found using the appropriate Green's function for the geometry such that

$$\theta(x,t) = \frac{\alpha}{k}\int_{\tau=0}^{t}\int_{x'} q'''(x',\tau)G(x,t|x',\tau)\,\mathrm{d}x'\,\mathrm{d}\tau \\ +\alpha\int_{\tau=0}^{t}\sum_{i=1}^{2}\frac{f_i(\tau)}{k_i}G(x,t|x_i,\tau)\,\mathrm{d}\tau \tag{2.4}$$

where the first term is the temperature response to an arbitrary generation rate, and the second term is the response to the external convective condition. The Green's function is given as

$$G(x,t|x',\tau) = \frac{2}{L}\sum_{m=1}^{\infty}\exp\left[-\frac{\beta_m^2\alpha(t-\tau)}{L^2}\right]\frac{\beta_m^2+^2}{\beta_m^2+^2+} \\ *\cos(\beta_m\frac{x}{L})\cos(\beta_m\frac{x'}{L}) \tag{2.5}$$

where the eigenvalues are determined from

$$\beta_m \tan\beta_m == \frac{hL}{k}. \tag{2.6}$$

The solution for the transient temperature distribution is formulated as

$$\theta(x,N\Delta t) = \frac{2L^2}{k}\sum_{m=1}^{\infty}\frac{F_m}{\beta_m^3}\sin(\beta_m)\cos(\beta_m x^*)\sum_{i=1}^{N}q_i'''\{\cdot\} \\ +\frac{2L}{k}\sum_{m=1}^{\infty}\frac{F_m}{\beta_m^2}\cos(\beta_m)\cos(\beta_m x^*)\sum_{i=1}^{N}f_i\{\cdot\} \tag{2.7}$$

where the $x^* = x/L$, and time has been discretized in terms of time steps of size Δt. The non-homogeneous functions q''' (volumetric generation) and $f = hT_\infty$ are piece-wise constant functions over each time interval Δt.

$$F_m = \frac{\beta_m^2+^2}{\beta_m^2+^2+}, \text{and} \tag{2.8}$$

$$\{\cdot\} = \{\exp[-\beta_m \mathrm{Fo}(N-i)] - \exp[-\beta_m \mathrm{Fo}(N-i+1)]\} \tag{2.9}$$

where $\mathrm{Fo} = \alpha\Delta t/L^2$.

To verify our Green's Function solution, we have compared the results of the foregoing transient model to that of a steady state model. The centerline ($x = 0$) and surface ($x = L$) temperatures were calculated for times up to $t = 20s$, which is long enough to reach steady state (see Figure 1). Two values for generation rate and the free-stream boundary temperature were selected to evaluate the ability of the transient response to match that of the steady solution, and all results were within 0.1% of the steady solution for 100 eigenvalues

($M = 100$). For simplicity the 1D slab was 1 unit long. This allowed the system to respond more quickly.

List of Constant Values Used		
Variable	Value	Unit
Biot Number	1	
Heat Transfer Coefficient	1	[W/m$^2/K$]
Thermal Conductivity	1	[W/m/K]
Geometrical Dimension	1	[m]
Thermal Diffusivity	1	[m$^2/s$]
Number of Eigenvalues	100	
Initial Temperature	0	[K]

Table 2.1: Table of 1D Solution Values Used

As can be seen in Figure 2, more eigenvalues result in a more accurate solution. For the below results, 100 eigenvalues were used. The conduction solution, while not an entirely realistic system, provides a framework for the neural network to control one temperature based on its relationship with another temperature.

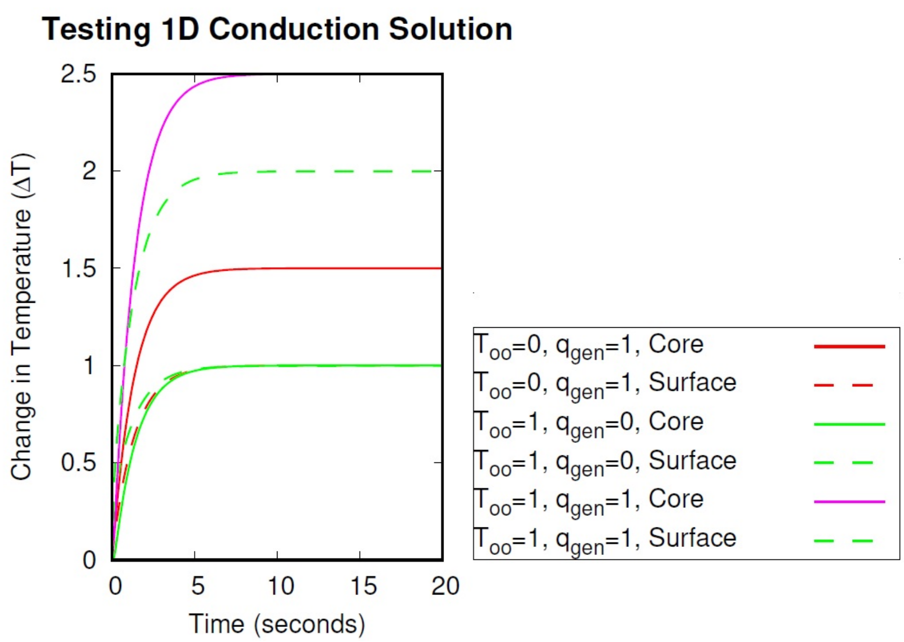

Figure 2.1: Transient response of centerline and surface temperatures for various generation rates and free-stream boundary temperatures

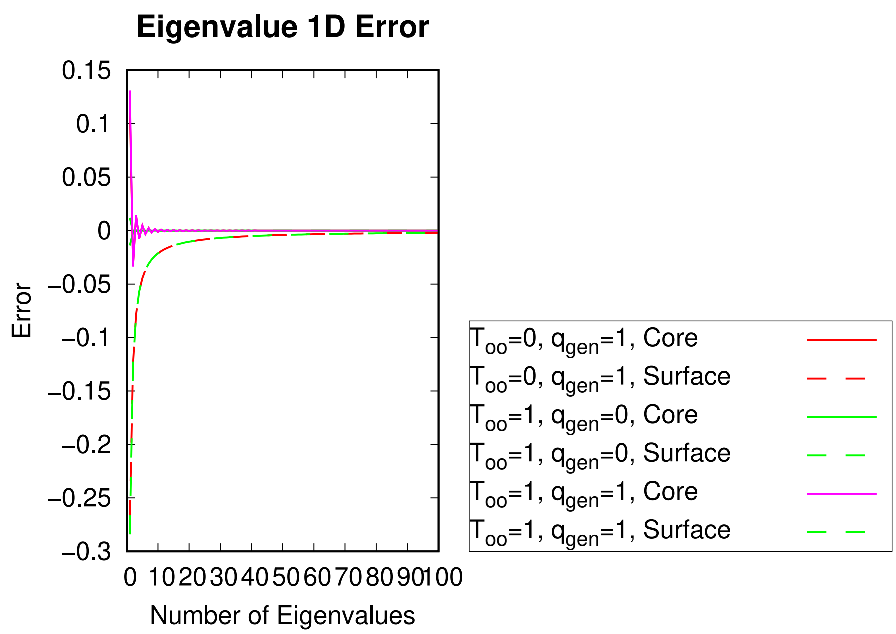

Figure 2.2: Eigenvalue 1D Error

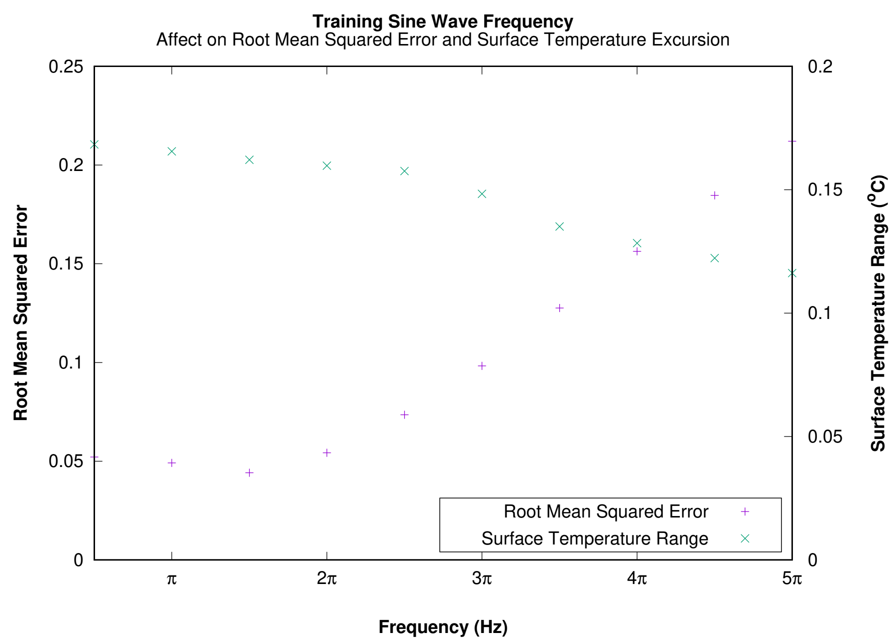

Figure 2.3: RMSE Relationship with Temperature Exposure

CHAPTER 3

PID Regulation of One Dimensional Model

A Proportional-Integral-Derivative (PID) controller maintains the desired internal temperature, of an oven for example, by adjusting the power going into the oven. A PID can regulate the internal temperature of any solid with volumetric generation. For a simple system like a plate, where there is an external temperature, ideal setpoint temperature, and some type of thermal response, a PID is all that is needed for the system to maintain a proper internal temperature accurately. If the system were more complex, like the human body, then a more sophisticated controller could be advantageous.

PID parameters are listed in Table 2 and results of the controlled system can be seen in Figure 1. Values

Variable	Value
Proportional	9
Integral	7
Derivative	0.5
PID Setpoint	1unitK
Time Constant	1

Table 3.1: Table of PID Values Used

for the PID were chosen to be P=9, I=7, and D=0.5 with a setpoint of 1 K because in multiple different environmental temperature patterns a PID controller with these values was able to maintain core temperature; these values were found to produce a generation that best maintained a core temperature of 1 K. The PID controller used for this demonstration was a modified version of IVMECH's. IVMech (2019)

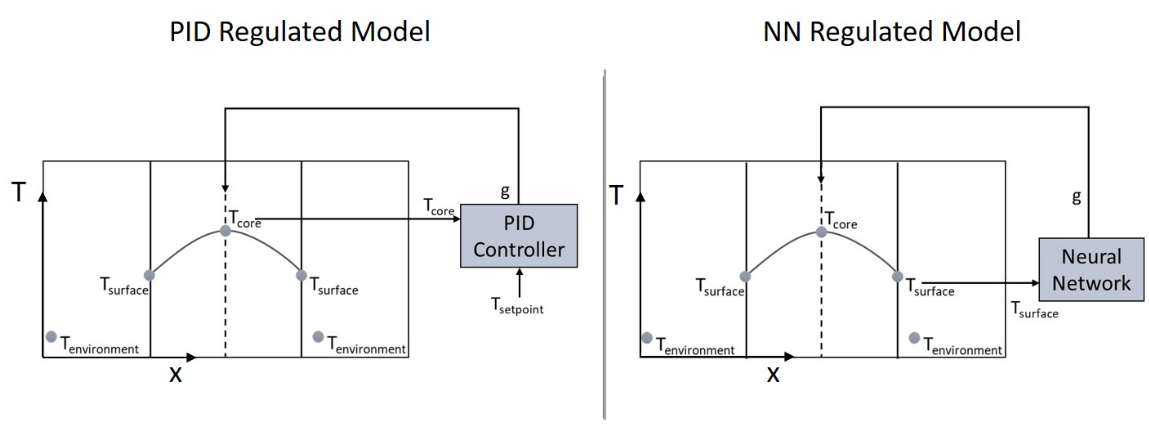

Figure 3.1: PID and NN Controls

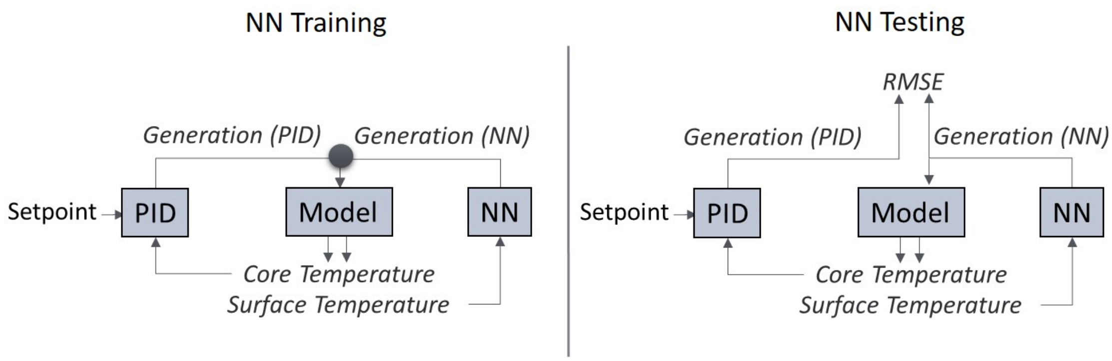

Figure 3.2: NN Training and Testing

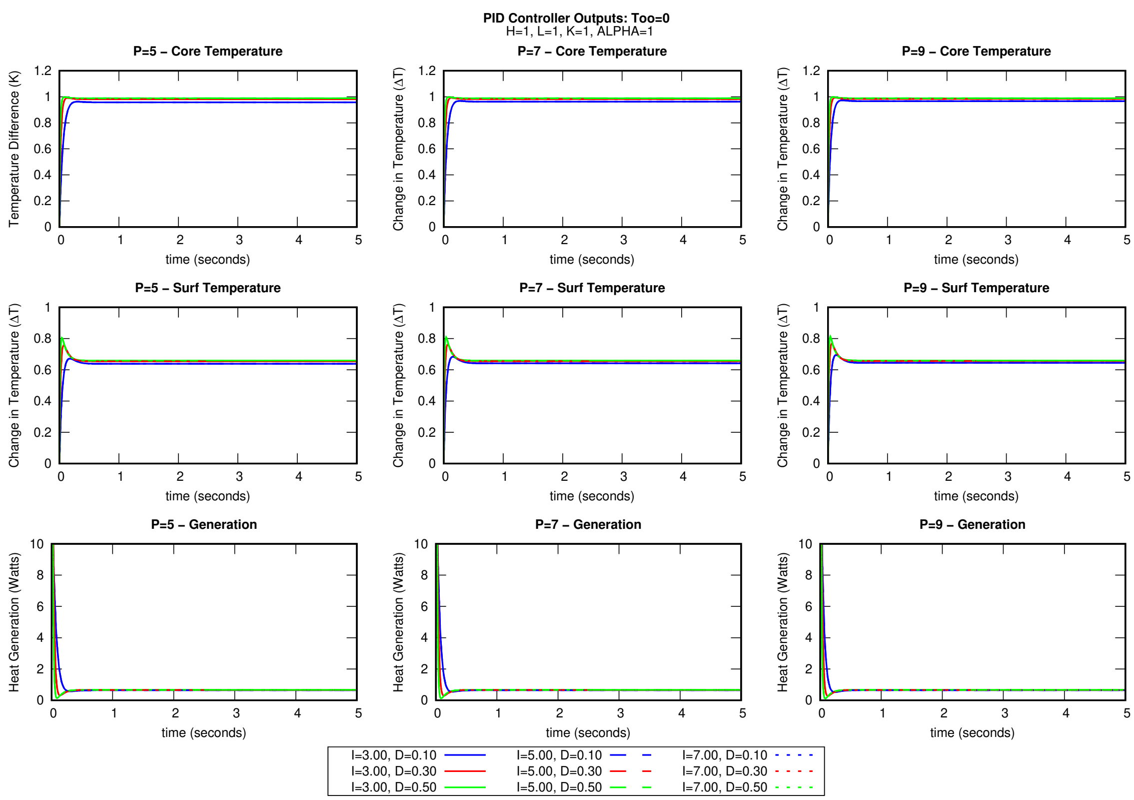

Figure 3.3: PID Value Variations

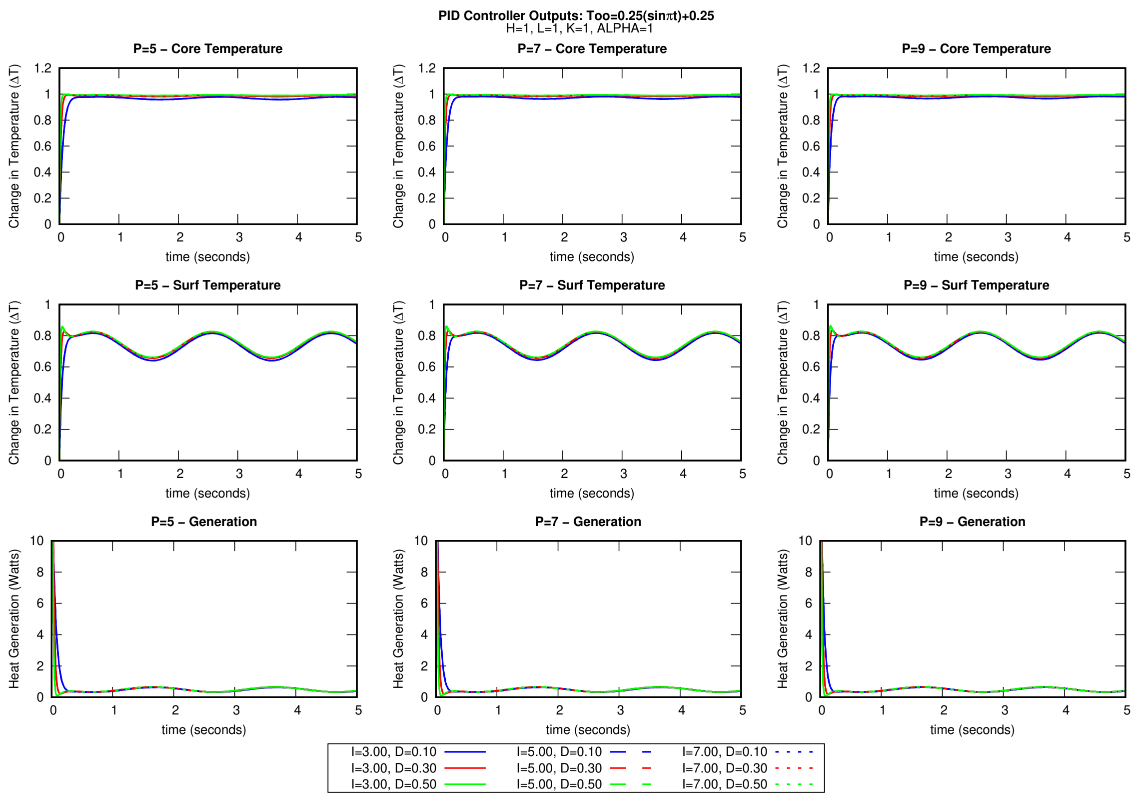

Figure 3.4: PID Value Variations (continued)

CHAPTER 4

PID Regulation of One Dimensional Model

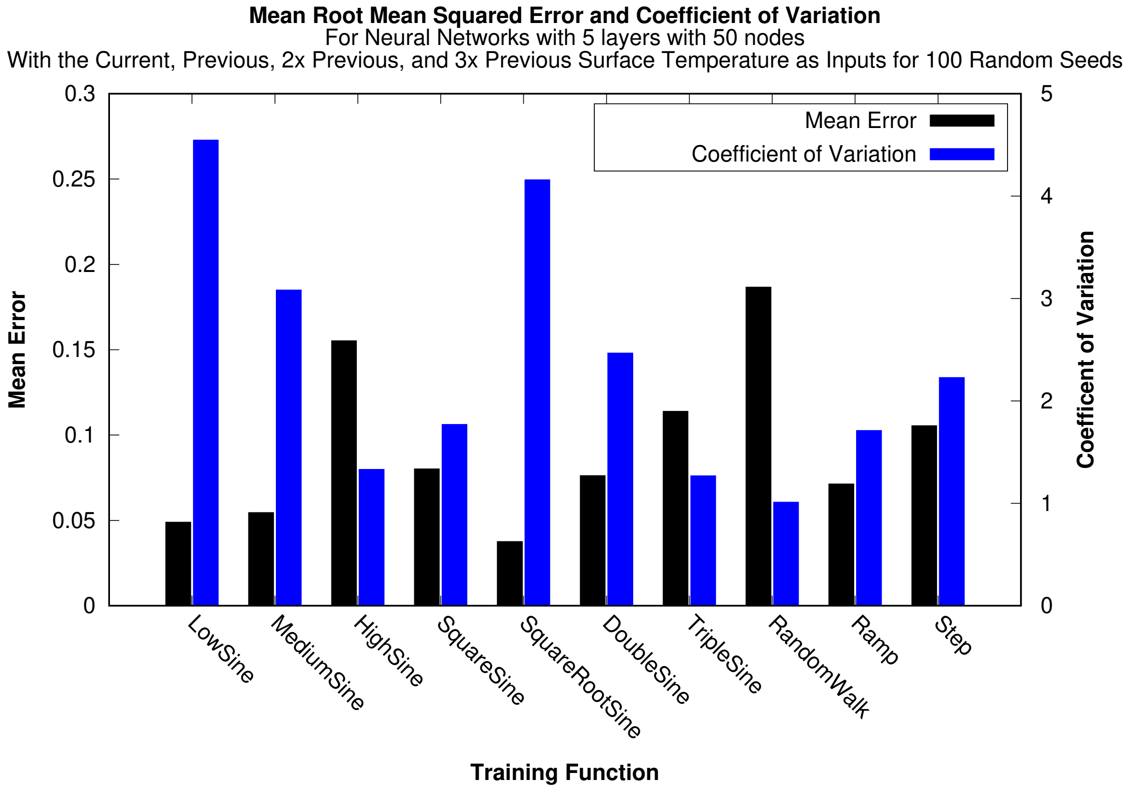

Figure 4.1: Error and CoV of NN Regulation

The goal of the analysis is to develop a neural network that can control a variable that can not be measured directly. Therefore, training data and feedback are not possible except through a physical model. In the current demonstration we will create a neural network that can adjust the volumetric heat generation in a one-dimensional planar solid to maintain an internal core temperature. The core temperature, however, is inaccessible; the surface temperature, which is measurable, is what varies due to varying external conditions (heat transfer coefficient or ambient temperature). Neural network controls are very effective when more relevant parameters are known, for example the value being adjusted or directly controlled. Predicting and regulating an internal response that is unknown is impossible without additional information. To account for the limited information that can be measured, an additional model is necessary. This model should be a physics-based model of the system in question. The additional information provided in the model will bridge the gap between known and unknown parameters resulting in a better functioning neural network.

The idea of using a distant but measurable temperature, instead of the temperature we ultimately want to control but can't measure, is unique to this work. Of course, if the measured temperature is unconnected to the controlled temperature, results are unpredictable. Therefore, we make use of a physics based model to augment the neural network's predictions, and this approach is known as a physics guided neural network (PGNN). Neural network controls theory uses networks to regulate unpredictable systems. A physics-guided neural network (PGNN), as outlined by Karpatne, is a strategy to use a physics-based model to enhance neural network predictions; the outputs of a physics based model are fed into the neural network along with real world data. There can also be a punishment in the training phase if the network suggests something that is not physically possible. For example while modeling the temperature distribution of a lake, the Karpatne group used the relationship between temperature, density, and depth of the water to train the neural network Karpatne and Vipin Kumar (2017). For our case, additional information through a physics-based model is provided indirectly during learning, unlike the Karpatne model where additional information is provided both as an input and during learning. Due to the transient nature of the problem, a current temperature and previous temperatures will be used as inputs. Allowing the neural network to receive the previous input helps control how aggressively the network responds. Recurrent neural networks (RNNs) allow remembering of previous information which is beneficial when making predictions for a system. RNNs also handle non-uniform data, varying environments, and generalization well Mandic and Chambers (2001). Our model has aspects of a simplified RNN because it only allows the input to be remembered not the response; we have chosen to use four inputs (current and three previous temperature) instead of a RNN to determine if the network could make satisfactory predictions only off temperatures, not previous generation responses. A long short-term memory network (LSTM) has a memory longer than a RNN but as will be demonstrated below, a longer memory is not advantageous to a problem with exponentially decaying behavior like that of a first-order system in time with a time constant that is commensurate with the time step between measurements. Hochreiter and Schmidhuber (1997) Using only surface temperature, we have trained a NN to maintain an unknown, ideal internal temperature of a one-dimensional plate while imposing varying environmental temperatures. The control for thermal generation would be fairly arbitrary if the NN is not aware of the temperature distribution within the plate. To develop a meaningful model, a heat transfer solution and successful controller are used to train the neural network. Both of these practices come from existing methods. The use of a physics based model to augment the NN's predictions is known as a physics guided neural network (PGNN). NN controls theory uses networks to regulate unpredictable systems. The idea of using a distant but measurable temperature is unique to this work. In Figure 9, a neural network trained in a low frequency sine wave environmental temperature pattern yields generation values that result in surface and internal temperatures that match very closely with its PID counterpart when tested in a double frequency sine wave environment.

This NN was provided with only surface temperatures but the surface temperatures at the current and three previous time steps. In our solution, the neural network (NN) was trained from the surface temperature data derived from the PID-controlled temperature solution. The environmental temperature (θ_∞) is specified as a piece wise constant function, and the generation rate is adjusted by the PID controller to maintain a fixed internal core temperature $\theta(x = 0)$. Because the core temperature is designed to remain constant, this is not a suitable training variable. Once trained, the neural network uses the computed temperature at $x = L$ (surface temperature) as the input and the generation rate (q''') as the output. An appropriately trained NN, therefore, is designed to maintain a constant internal temperature ($\theta(x = 0)$) by adjusting the generation rate and measuring the external temperature ($\theta(x = L)$). This is analogous to the HBTM/NN trying to maintain internal core temperature by adjusting the metabolic rate using the external skin temperatures as the only measurements. The training process of the ANN can be seen in Figure 5. The calculated surface temperature and corresponding PID generation values were used during the training period for the ANN, and the ANN received the same surface temperature calculated by the PID controlled model. Then the NN created a unique generation response, and core temperature was calculated using the physical conduction model. The neural network was implemented using the `python` module `SKLearn`. Because the surface temperature is not a direct proxy for the core temperature, which is what we really want to control, we had to include multiple time steps of surface temperatures. To help us understand how the variability in the external temperatures affects the efficacy of the training data, we chose several functions for the environmental temperature. These different simulated environmental temperature patterns can be found in Table 5. Allowing the neural network access to current and three previous time steps was chosen to provide more information to the network.

List of Constant Values Used	
Variable	Value
Number of Layers	5
Total Nodes	250

Table 4.1: Table of NN Values Used

Input and Output Guide						
PID Input	PID Out	PID Result	NN Input	NN Out	NN Result	NN Check
$T_{core,PID}$	q'''_{PID}	$T_{surf,PID}$	$T_{surf,PID}$	q'''_{NN}	$T_{core,NN}$	$T_{surf,NN}$

Table 4.2: Table of Inputs and Outputs

Tables 6 and 8 also display the drawbacks of only providing the neural network with surface temperature. The performance improves when core or core and surface temperatures are input than when only surface temperature is known. For this case, surface temperature was still chosen for the input to explore what was possible despite known drawbacks.

Simulated Environmental Temperature Patterns	
Environmental Temp Pattern	$\mathrm{T}_{oo} Function (where \omega = frequency)$
Low Frequency Sine	$\mathrm{T}_{oo} = 0.25 \sin(\pi t) + 0.25$
Medium Frequency Sine	$\mathrm{T}_{oo} = 0.25 \sin(2\pi t) + 0.25$
High Frequency Sine	$\mathrm{T}_{oo} = 0.25 \sin(4\pi t) + 0.25$
Constant	$\mathrm{T}_{oo} = 0$
Step	$\mathrm{T}_{oo} = for 1 sec each 0.5, 0.4, 0.3, 0.2, 0.1$
Ramp	$\mathrm{T}_{oo} = -\frac{1}{10} t + 0.5$
Square Sine	$\mathrm{T}_{oo} = 0.25 \sin\left(0.5\pi t^2\right) + 0.25$
Square Root Sine	$\mathrm{T}_{oo} = 0.25 \sin\left(\pi \sqrt{t}\right) + 0.25$
Double Sine	$\mathrm{T}_{oo} = 0.20 \sin(\pi t) + 0.05 \sin(10\pi t) + 0.25$
Triple Sine	$\mathrm{T}_{oo} = 0.15 \sin(\pi t) + 0.05 \sin(10\pi t) + 0.05 \sin(20\pi t) + 0.25$
Varying Frequency	$\mathrm{T}_{oo} = 0.25 \sin(\omega t) + 0.25$

Table 4.3: Table of Varying Environments Considered

CHAPTER 5

Results of the One Dimensional Model

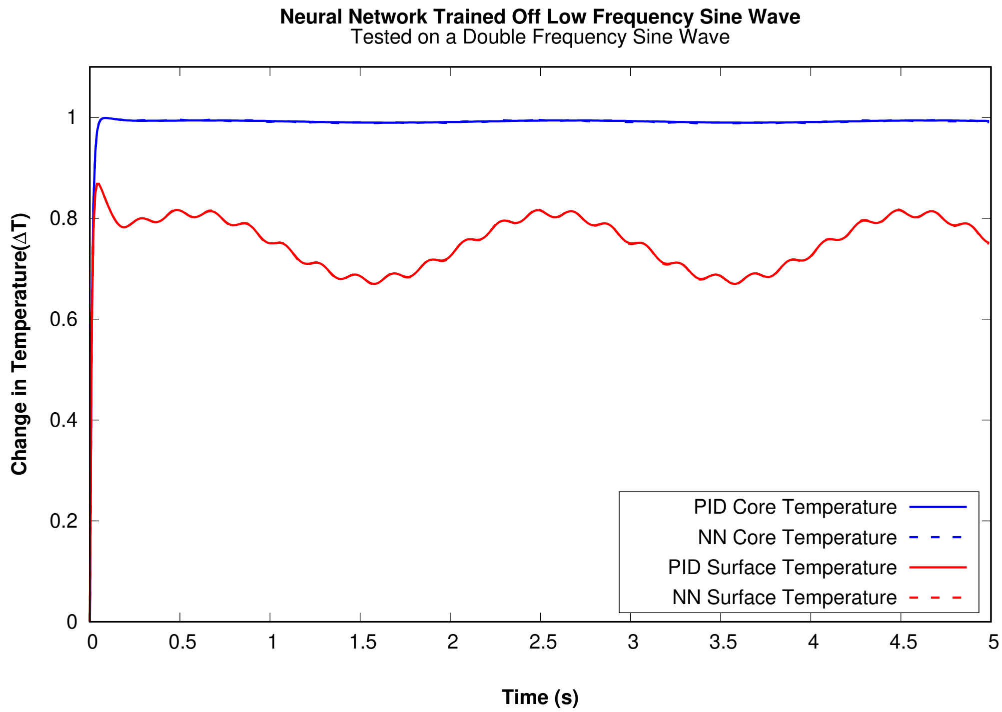

Figure 5.1: 1D PID vs NN Demonstration

To verify that training a neural network using outputs that are unmeasurable is feasible, we have devised a data source using a one-dimensional conduction solution for a plate coupled with a PID controller. The PID controller is operated to maintain a constant internal temperature, which we assume is measurable for the fabrication of training data, by adjusting the internal volumetric generation. (Much like a PID controller maintains a constant temperature in an oven.) The output of the PID controlled plate, however, is surface temperature. Using only surface temperature, we have trained a neural network to maintain the internal surface temperature without any knowledge of what that temperature is, while imposing varying environmental temperatures. In addition to being unable to provide the neural network with the preferred input, the temperature distribution throughout the solid will also be unknown to the network. Regulating a system like this one is not new; neural networks have been used in control problems before to regulate a process that is governed by an unknown function. In this case the controller will be a PID controller. A PID-controlled forward transient conduction solution was used to fabricate data to train the NN. The core temperature was used as the set point, and the controller selected higher or lower generation rates to maintain the core temperature as the environmental temperature was varied. The surface temperature, which is the training data for the NN, was recorded at each time step. To determine the efficacy of the trained neural network, we compared the behavior of the neural network/conduction system to the PID/conduction system. In both cases the controller (either the NN or the PID) determined the generation rate, which was input into the conduction solution. Of course the primary goal of the PID and the NN was to adjust the generation rate to maintain a constant core temperature. Therefore, we can compare the generation rate and the core temperature derived from both strategies. Keep in mind that the NN was trained on the external surface temperature history of the PID-controlled system, not the core temperature itself. Consequently, we may expect deviations from the constant core temperature since the NN knows nothing about that variable except that the external surface temperature, the core temperature and the generation rate are all related through the conduction model. If the NN is designed correctly, we should be able to indirectly control the core temperature with the NN as long as the conduction physics is included in our control strategy. To generate training data, we imposed a varying environmental temperature ($T_\infty(t)$) on the conduction solution so that the PID controller would change the generation rate ($q'''(t)$) to maintain the core temperature $[T(x=0)]$. The conduction results for the external surface temperature $[T(x=L)]$ and the PID-controlled generation rate were recorded as training data. The functional form of the transient environmental temperature, however, could affect the weights and ultimate performance of the NN. Therefore, we tested several forms of a varying environmental temperature to see what characteristics would produce a better NN. Selecting a training set that will prepare the NN for the testing phase is an important step. To evaluate how our system would respond to different training and testing environments we ran the following analysis. For demonstration purposes, Tables 5 through 8 show different minimum RMSE values for different combinations of training and testing functions. First we will look at temperature patterns used then the use of historical temperature data and finally just for interest the possibilities if an internal and surface temperature were provided instead of only surface temperature. Table 5 shows a NN trained with the surface temperature when the model is in a low-frequency sine-wave temperature environment; $T_{oo} = 0.25\sin(\pi t) + 0.25$. When the already trained NN was tested in five different environmental temperature patterns the minimum internal temperature RMSE can be seen in Table 5 with the generation minimum RMSE in parenthesis. If the system is trained with a low frequency sine wave pattern then the NN will perform best in (1) a constant (2) random walk (3) double sine wave (4) high frequency sine wave and finally (5) low frequency sine wave environment. Compared with Table 6 where a NN is trained in a high-frequency sine-wave temperature environment; $T_{oo} = 0.25\sin(4\pi t) + 0.25$; the NN performs best in (1) high frequency sine wave (2) double sine wave (3) low frequency sine wave (4) random walk then (5) constant temperature based on the minimum RMSE values for core temperature. The trained neural network produces more accurate results when tested on the testing data than being tested on the same training data it was just saw. This implies the model is likely not overfit. For example, the higher frequency environment seemed to be overfit. If the model were overfit then the neural network would perform best when presented with a situation identical to its training environment; it would be too specialized for only one pattern of inputs instead of open to and useful for analyzing unfamiliar patterns.

When deciding if only the current surface temperature should be provided to the NN or if previous, historical information would be beneficial Tables 5 and 7 can be compared. Both of these tables show data for NNs trained in Low Frequency Sine Wave (LFS) environments but Table 5 only uses the current temperature whereas Table 7 provides historical temperatures as well. There is improvement during all testing environments except for steady temperature with additional information. We believe this is because it was the only environment where the previous time step was the exact same temperature as the current.

Including historical data from the previous time step yielded much better results as can be seen in the difference from Table 5 to 7. Moving to include an additional previous time step resulted in another reduction in error but not as significant. When the current and three previous temperatures were included there was a very minor improvement to the performance during testing for some but not all testing functions; for environments that did not show any benefit to including three previous time steps the results did not worsen, just stayed the same.

Surface temperature is the only measurable temperature in the intended medical application but for demonstration purposes we share what improvements there can be if using core and surface temperatures. Tables 5 and 8 are both trained with a LFS environment. Both networks are input the current surface temperature but the NN summarized in Table 8 is also given core temperature at the same time step. There is a significant improvement in the NN accuracy for all cases here. This makes sense that core temperature is easier for the NN to regulate when it is a known quantity.

Trained with LFS Wave Environment and Current Surface Temperature				
Constant	LFS	HFS	DS	RW
0.0017(0.0057)	0.0112(0.0308)	0.0092(0.0919)	0.0091(0.0295)	0.0057(0.0160)

Table 5.1: Results of Low Frequency Sine Wave, One Timestep

Trained with HFS Wave Environment and Current Surface Temperature				
Constant	LFS	HFS	DS	RW
0.0939(0.0817)	0.0230(0.0592)	0.0072(0.0741)	0.0183(0.0480)	0.0246(0.0139)

Table 5.2: Results of High Frequency Sine Wave, One Timestep

After a range of simulations several factors were found to result in the best NN. Combinations with more than two layers and 10 nodes per layer were found to give the best results as can be seen in Figure. The

Trained with LFS Wave Environment and Current+1 Previous Temperature				
Constant	LFS	HFS	DS	RW
0.0017(0.0058)	0.0009(0.0029)	0.0047(0.0511)	0.0011(0.0281)	0.0012(0.0156)

Table 5.3: Results of Low Frequency Sine Wave, Two Timestep

Trained with LFS Wave and Current+1 Previous Surface+Core Temperature				
Constant	LFS	HFS	DS	RW
0.0002(0.0003)	0.0001(0.0005)	0.0004(0.0023)	0.0002(0.0009)	0.0002(0.0006)

Table 5.4: Results of Low Frequency Sine Wave with Additional Inputs

random seed used to generate initial weights was found to not have an impact on the final results.

Figure 8, shows the root mean squared error (RMSE) and coefficient of variation (CoV) for 2,000 runs with the listed training function used as environmental temperature.

CoV is the ratio of standard deviation to the mean and was selected as a measure because it is dimensionless and does not require a knowledge of the mean to be useful to the reader. This is beneficial because while our different temperature environments do cover similar ranges, their means are not necessarily identical while all the means are not near zeros.

Responses from neural networks trained in a square sine wave and decreasing ramp environment can be found in the appendices.

Neural Network Trained in Low Frequency Sine Wave Environment		
Test Environment	MinRMSE for T_{core}	Environmental Temperature Function
Constant	0.0019	$T_{oo} = 0$
Low Frequency Sine	0.0006	$T_{oo} = 0.25\sin(\pi t) + 0.25$
High Frequency Sine	0.0035	$T_{oo} = 0.25\sin(4\pi t) + 0.25$
Double Sine Wave	0.0009	$T_{oo} = 0.20\sin(\pi t) + 0.05\sin(10\pi t) + 0.25$
Random Walk	0.0008	$T_{oo} = Random$

Table 5.5: Performance of NN Trained in LFS fifty nodes, five layers

Depending on the anticipated testing values a training set can be chosen accordingly. The NN itself can also be fine tuned to a situation by changing the number of nodes and layers, etc.

The ideal training function would have both a low RMSE and CoV when tested in such a wide range of temperatures. The top three training patterns from the data were low frequency sine wave, square sine wave, and decreasing ramp. Low frequency training data resulted in a wider range of surface temperatures which led to a higher performing neural network. An environmental temperature that changed more slowly also seemed beneficial. The penetration depth $\delta_p = \frac{\alpha}{\omega}$ or $\delta_p = \frac{1}{\alpha}$ for the low frequency sine wave environment was greater than for other possible training environment. A neural network was successfully trained how to maintain a set internal temperature despite fluctuating environmental temperature and only knowing external temperature. The network was able to perform well without knowing the relationship between internal and external temperature. The temperature distribution was originally an unknown for the neural network. The internal core temperature regulated by the neural network nearly matches that of the PID controlled model even though different temperatures were given to the two controllers. The neural network was input surface temperature while PID received core temperature. The neural network learns the relationship between an input and what the user wants to predict. The generation recommended by the neural network is not as consistent as the heat generation suggested by the PID controller but both controllers maintain very similar core temperatures which was the key concern of the project.

CHAPTER 6

Human Body Thermal Model

One of the first Human Body Thermal Models (HBTMs) was developed by J.A.J. Stolijwick for NASA. This model divides a person into 25 nodes; these nodes are representative of body parts, such as the head or hand, as well as the blood. The arm, for example, is represented by four nodes; the outer node being treated as the skin with heat exchange between the environment being accounted for through evaporation, convection, and radiation. This model is tuned by adjusting parameters that are considered representative of physiological functions such as sweating or vasoconstriction. Stolwijk (1971) Tanabe and group made a similar model, except it was designed for HVAC predictions. S.Tanabe and M.Konishi (2002)

All existing HBTMs have either operated by a series of non-physical parameters being adjusted to produce results that fit with human response or through the solving of heat transfer equations. Our HBTM works using the second approach. Each segment of the body is treated as a cylinder. Each cylinder has an artery carrying blood from the center of the body to the extremities and another carrying the blood back; this is modelled as a counter flow heat exchanger. The outlet temperature of the leading blood and the inlet temperature of the returning blood are considered equal. There are two concentric cylinders surrounding these simulated arteries. The inner cylinder's temperature takes into consideration the heat flow from the arteries as well as the conduction with the outer cylinder and the internal generation. The outer cylinder can be considered the skin. The outer layer's temperature is found using the heat conduction from the inner cylinder, internal generation in that layer, and the conductive loss or gain from the surroundings. Conductive instead of convective cooling was considered based on a planned experiment with a partnership at the Damon Lab. The mechanisms for thermal regulation laid out by Morrison and Nakamura were also considered when discussing how to best structure the model. Morrison and Nakamura (2018)

$$q_{II}'''V_{II} + \frac{T_I - T_{II}}{R_{I-II}} = \frac{T_{II} - T_{oo}}{R_{ext}} + (\rho V c_p)_{II} \frac{T_{II} - T_{II,old}}{\Delta t} \tag{6.1}$$

$$q_I'''V_I + \frac{T_{v,i} + T_{v,o}}{2R_{v-I}} - \frac{T_I}{R_{v-I}} + \frac{T_{a,i} + T_{a,o}}{2R_{a-I}} - \frac{T_I}{R_{a-I}} = \frac{T_I - T_{II}}{R_{I-II}} + (\rho V c_p)_I \frac{T_I - T_{I,old}}{\Delta t} \tag{6.2}$$

$$
\begin{aligned}
mT_{v,i} + UA\left(\frac{T_{a,i}+T_{a,o}}{2} - \frac{T_{v,i}+T_{v,o}}{2}\right) = {} & \frac{T_{v,i}+T_{v,o}}{2R_{v-I}} - \frac{T_I}{R_{v-I}} + mT_{v,o} \\
& + \left(\frac{\rho V c_p}{2\Delta t}\right)_v [(T_{v,i}+T_{v,o}) - (T_{v,i,old}+T_{v,o,old})]
\end{aligned}
\tag{6.3}
$$

$$
\begin{aligned}
mT_{a,i} + UA\left(\frac{T_{a,i}+T_{a,o}}{2} - \frac{T_{v,i}+T_{v,o}}{2}\right) = {} & \frac{T_{a,i}+T_{a,o}}{2R_{a-I}} - \frac{T_I}{R_{a-I}} + mT_{a,o} \\
& + \left(\frac{\rho V c_p}{2\Delta t}\right)_a [(T_{a,i}+T_{a,o}) - (T_{a,i,old}+T_{a,o,old})]
\end{aligned}
\tag{6.4}
$$

$$
T_{a,o} = T_{v,i} \tag{6.5}
$$

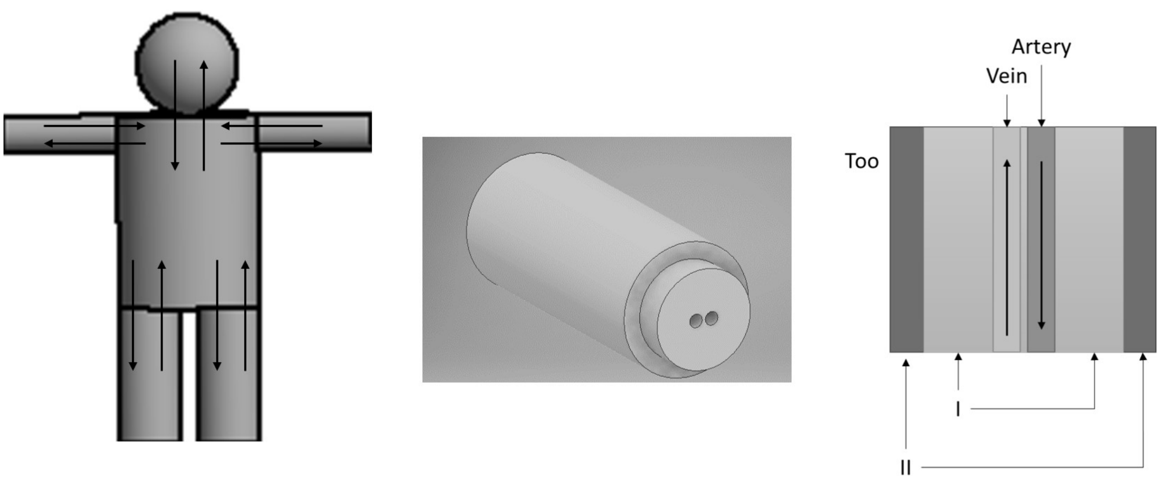

Figure 6.1: HBTM Internal Details

One possible controller to consider for a more complicated regulation is a neural network (NN). NNs were inspired by the human brain and to some degree designed to mimic our brains' decision making capabilities. Using a NN to regulate a thermal model of a human body (HBTM) could prove beneficial to medicine,

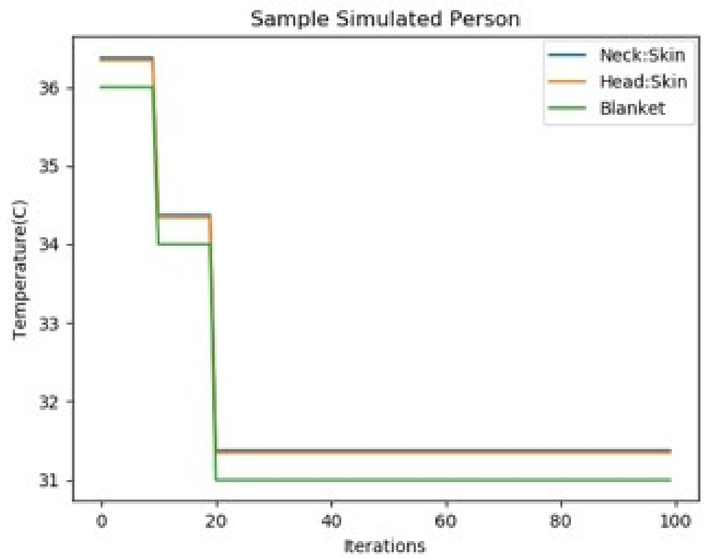

Figure 6.2: HBTM Performance

particularly regarding any diseases or treatments with thermal considerations. The NN could anticipate when someone would shiver or sweat based on the external temperature their body is sensing. The preliminary work to train a neural network to thermally regulate a human body thermal model has gone well. A possible flow to integrate experimental data into the HBTM-NN process is shown.

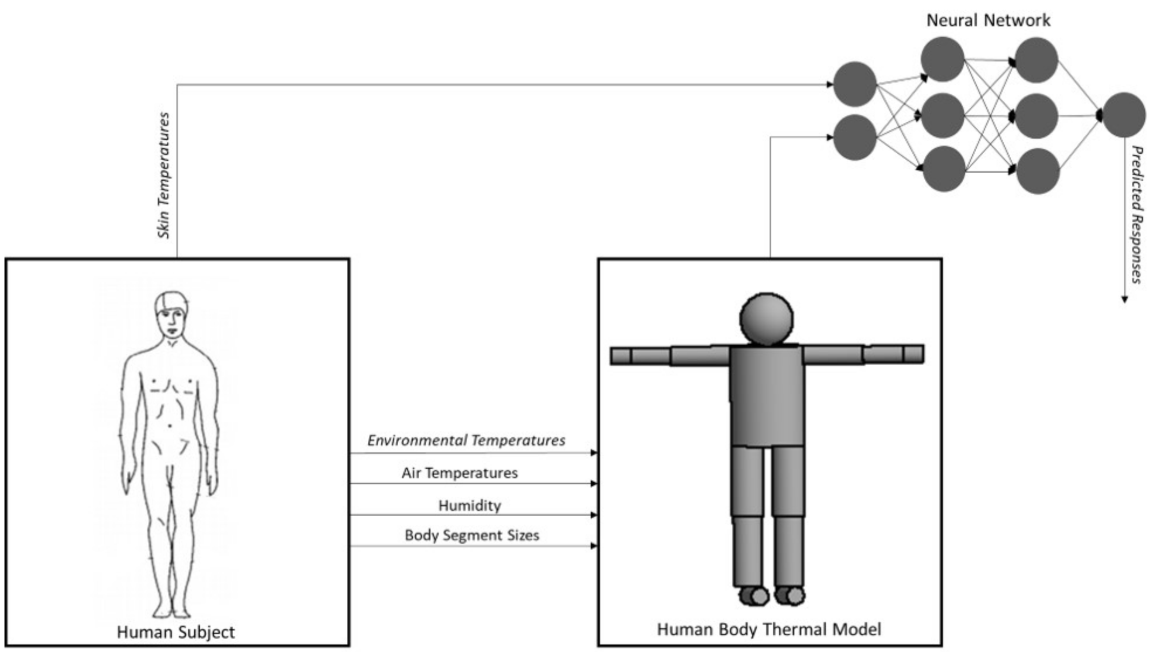

Figure 6.3: HBTM-NN Possible Flow

CHAPTER 7

Conclusions

The only information directly input to the neural network was surface temperature but additional information was available indirectly; this is an advantage of PGNNs. By training with the PID generation values, which maintained close to a set core temperature, the neural network was taught what response should be recommended for different surface temperature patterns; after training, the neural network had been imbued with the relationship between the surface and core temperature (the conduction solution), the set point for the core temperature, and how much generation was needed to maintain that ideal internal temperature in varying environments. PGNNs allow an entire system to be folded into the system with a single input. However, this PGNN is unique in that it receives one parameter and controls another.

Based on the success of regulating an inaccessible temperature of a 1-D model with a peripheral temperature and a neural network, the group anticipates being able to apply this same practice to a human body thermal model. With this, simulated or experimental human body skin temperatures could be recorded and internal responses predicted. Insights into the human body's thermal responses could be of interest for several health based reasons. The preliminary work controlling the human body thermal model with a neural network has been successful.

Using a neural network to learn each individual's internal response patterns will be advantageous because there are many unknowns of how a brain keeps its body alive. As an observer, the brain seems to effortlessly regulate the constant, inner workings of the body. In a similar way, neural networks can predict and control complex systems with ease. A neural network seems to be the best method of recreating the controls of the autonomic nervous system and developing a model of the brain. Many of the internal functions of the human body either cannot be quantified or measured without causing harm. This makes training a neural network that can mimic human physiology very difficult. If internal human body responses could be measured, learning and moderating the internal workings of a system would be a straight forward problem. However when the internal responses are either inaccessible or unmeasurable then maintaining a set state becomes challenging. A desire to understand the inner world of a body frequently occurs in the medical field, where ailments are often unobservable without aid. Similar to how medical imaging allows the inner layout of a body to be seen without operating, predicting internal temperatures and responses from something innocuous like skin temperatures could be a non-invasive way to increase understanding of human physiology. The human body has a number of internal responses that are known but cannot be quantified with current devices. Shivering, sweating, vasoconstriction, and vasodilation are all responses that need to be estimated in a human body model. Many of these responses are in effort to maintain an ideal core temperature. The model will hopefully be making thermoregulation decisions similar to the brain.

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