Biosphere 2 Ocean: Optimization of Heat Exchange

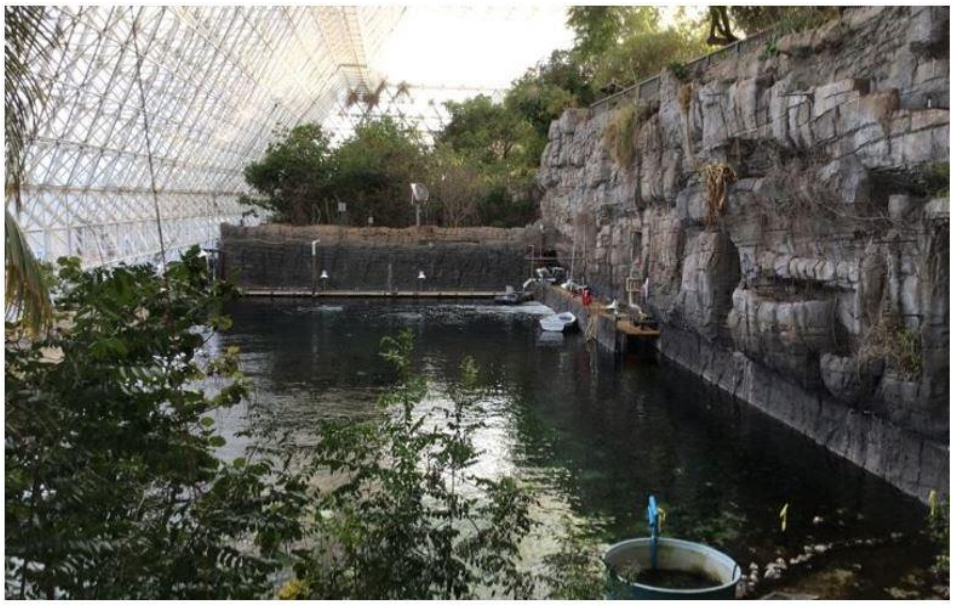
Dr. Ildar Gabitov

MATH 485

Final Report

Attn: John Adams, Deputy Director, Biosphere 2, University of Arizona

12 May 2020



"Envisioning science for reef solutions in the Biosphere 2 Ocean" by J. Cole, R. Gates, and workshop participants

Team: Lyra Troy, Sasha Sepulveda, Carl Solway

Biosphere 2 Ocean Background

The Biosphere 2 contains several housed ecosystems used in large-scale experimentation to better understand Earth's natural ecosystems. One of these vital ecosystems is the ocean habitat, known as the Biosphere 2 Ocean (B2O). Using the B2O, researchers at Biosphere 2 can study several important mechanisms that mimic Earth's oceans. One such research area involves coral, and how they thrive in different ocean conditions. The widespread death of corals has been closely tied to rising ocean temperatures; the B2O allows ecologists to study coral in response to warming temperatures in a simulated ocean environment. Hence, it is important for researchers to be able to control the temperature of the large-scale experimental ocean.

Introduction

The B2O has a water volume of 676,000 gallons and heated/cooled water is let in through one inlet in the corner via a single main pump at a flow rate of 380 GPM. Currently, the B2O setpoint temperature is 75°F ± 0.20°F. The water is mixed evenly with a mixer in the center and there is a temperature sensor near the well-mixed water. At the other end of the B2O, the water exits through one outlet to a pump, and is cycled back to the heating/cooling loop.

The water flow diagram for the B2O heating/cooling loop is shown below in Figure 1.

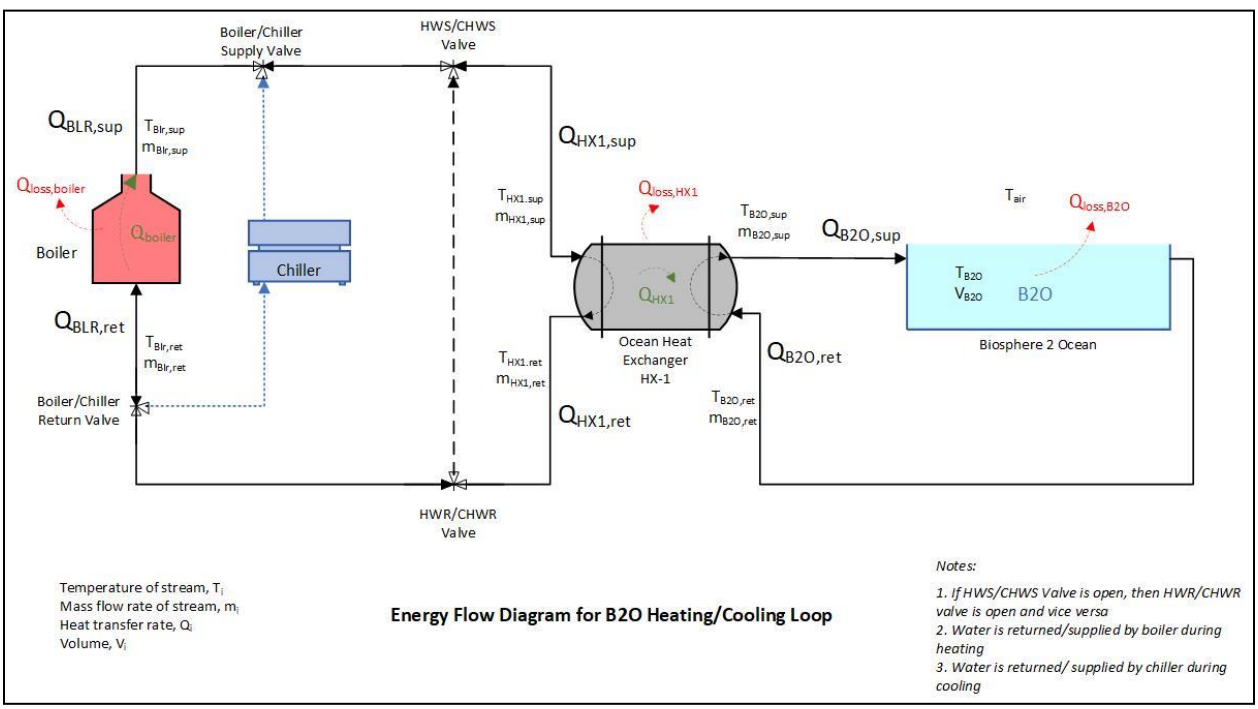


Figure 1: Energy Flow Diagram for B2O Heating/Cooling System

In the system, there is: the B2O, one *Ocean Heat Exchanger* (HX-1), a *Boiler*, and a *Chiller.* The heat exchanger HX-1 is a titanium plate-and-frame countercurrent water-water heat exchanger. The water being supplied to HX-1 and the water in the B2O circuit do not physically mix; the heat carried by one

stream of water is transferred to the other stream of water via counter-current water-water heat exchange. As denoted by Figure 1, this transfer of heat is Q_{HX1}. The temperature and flow rate of water entering HX-1, $T_{HX1,sup}$ and $m_{HX1,sup}$, are recorded every 15 minutes by a thermostat and flow meter. The temperature of the water leaving HX-1, $T_{HX1,ret}$, is also recorded every 15 minutes by a thermostat. The temperature and flow rate of the water entering the B2O, $T_{B2O,sup}$, is recorded by a thermostat and the flowrate is constant (380 GPM).

The temperature of B2O is controlled by HX-1, which sources water from either the boiler or chiller contained in the Biosphere 2 energy center. Once the water entering HX-1 has transferred heat, it is returned to either the energy center (containing the boiler and chiller) or to HX-1 supply water again.

There are two loops that the system can use; an external (open) loop and an internal (closed) loop. During open-loop heating/cooling, the *Hot Water Supply/Chilled Water Supply* (HWS/CHWS) and *Hot Water Return/Chilled Water Return* (HWR/CHWR) valves are open, in which water from the boiler or chiller enter HX-1. During closed-loop heating/cooling, which corresponds to the B2O requiring neither heating or cooling, the HWS/CHWS and HWR/CHWR valves are closed, and the water flows in an internal loop in HX-1. The closed loop circuit is denoted by the dashed line in Figure 1 above; water travels along the black dashed line during closed loop heating/cooling.

During open-loop heating/cooling, when the B2O needs to be heated, the *Boiler/Chiller Supply* and *Boiler/Chiller Return* Valves will be opened from the boiler, and the heat exchanger will draw and return heated water to and from the boiler. When the B2O needs to be cooled, the same valves will be opened from the chiller, and the heat exchanger will draw and return cooled water to and from the chiller, denoted in Figure 1 by the blue dashed line.

Currently, the temperature of the B2O is manually controlled by experienced operators. The valves in the system can be manually shut or open, and by observing the change in the B2O temperature, the operators in the energy center rely on experience when deciding to open or close these valves. When the experienced operators observe a certain rise or drop in the B2O setpoint temperature, they allow the flow of water from either the chiller or boiler entering the heat exchanger to be supplied to B2O.

Problem Statement

While the researchers are very interested in studying the coral, little attention is given to the energy demand to continuously heat and cool the B2O. This project was created when concern rose from John Adams, Biosphere 2 Deputy Director, about the high amount of energy needed to keep the B2O heated and cooled, and ways to optimize the energy usage while maintaining the desired temperature of B2O.

The amount of energy required to continuously maintain the B2O setpoint temperature is very large. The temperature of the B2O constantly changes and largely depends on the time of the day and the time of the year. For this reason, the B2O relies on chilled or heated water that comes from either the boiler or the chiller in the Biosphere 2 energy center. In the summer, the chiller uses around 1 megawatt (1,000,000 Watts) of energy per day, and in the winter, the boiler can use up to 3 megawatts (3,000,000 Watts). It is evident that energy equates to cost; as the energy requirement remains high to keep the setpoint of B2O constant, the cost to operate the chiller and the boiler remain high as well.

While experience is involved and there is a vague schedule and guidelines, there is no formal model in place dictating at what conditions, when, and how much the valves in the system should be opened or

shut. Often, manual control of such large systems can equate to large energy losses, which in turn raises the operating costs.

In addition, little is currently known about which heating/cooling loop system is more energetically efficient. For example, if the B2O requires heating, one may wonder if it is energetically more efficient to keep the internal heat exchanger loop pre-heated at a warm temperature to consistently feed into B2O. Or, a contrary idea may be to wait for the B2O to reach a lower setpoint temperature, then to add a large amount of newly heated water in a smaller interval of time.

Currently, no model of energy transfer in the B2O system exists and a model can only be achieved through deciphering advanced engineering schematics supplied by Biosphere 2, along with matching large data sets to several sensors in the schematics.

In addition to creating a model, another method that can be utilized is through machine learning. A computer algorithm would be created that, using given data from B2O as well as data from a simulation, could be continually trained to produce the optimal output for the given data. Here, the machine learning would not require a model, but rather would take information in about the state, and make the best possible decision for future outcomes.

Project Objectives

The goal of this project is to provide the framework in order to optimize the energy consumption used by B2O in order to reduce cost while still maintaining the desired setpoint temperature. Before optimization can be achieved, a thorough modeling of the system needs to be established and understood.

The objectives and deliverables of this project include:

1) Define optimization for the B2O system
2) An energy flow schematic of the B2O system
3) A developed energy balance around the B2O system
4) A simple thermodynamic model relating temperatures and mass flowrates in the system
5) Provide an estimation model to match actual data for a specified timeframe
6) An analysis of the energy losses in the energy balance

With the completion of these objectives, further progress can be made by future groups in modeling the B2O system by accounting for more system variables. With a complete model in which all parameters are included, a clear understanding between energy usage and the time of the day and year can be achieved, and optimization can be achieved.

With regards to machine learning, the objectives of the project are the same in regards to understanding the B2O system, but it focuses more on:

1) Find a relationship between inputs and outputs
2) Develop a working program that can be trained using data gathered from B2O
3) Use data to initially train the program
4) Continue to develop the program into a predictive program and can be iteratively optimized throughout the year when given a constant influx of new data.

Optimization Rationale

As stated earlier, it is unknown which heating/cooling loop is more energetically efficient. When optimizing energy consumption, it is important to know which system is energetically more efficient, as that system will ultimately lead to less energy being wasted and reduced operating costs.

The key to optimization for the B2O system lies within the heat equation, denoted below.

$$u_t = c^2 u_{xx} \tag{1}$$

The heat equation describes how the distribution of heat evolves over time in an object. The equation can be derived in a number of ways, but will not be addressed due to the scope of this project. Instead, the heat equation will be used as an acceptable premise to understand heat transfer.

The heat equation states that, the rate at which an object heats up is proportional to the temperature difference of the object to the surroundings. The larger the temperature difference, or the larger the gradient, the faster the net flow of heat energy in the system occurs. As the temperature gradient decreases, the heat flow rate also decreases in time. For this reason, essentially, it is more efficient to reheat a certain temperature than to maintain a constant temperature. HX-1

In the B2O system, the object is the B2O, in which contains an amount of heat energy that changes with time; temperature increase and decrease throughout the day. The temperature gradient of the system is the difference between the B2O temperature and the B2O water supply temperature; the larger the temperature difference, the faster the B2O will heat or cool.

Connecting the heat equation to real-time cost can ultimately be achieved through examining the energy used over time. Real-time cost tells us that the energy usage of a system, like electricity, is often metered over time. The more energy that is used in time, the higher the cost for energy usage. The heat equation tells us that a larger temperature gradient results in faster energy flow, or more energy in a smaller amount of time. Therefore, without going into mathematical depth and without the need to solve the heat equation, it can be concluded that the faster the flow of energy, the lower the energy cost is needed for a system.

This means that the B2O temperature should be allowed to reach it's lowest setpoint temperature, to maintain a larger temperature gradient, and then should receive heating/cooling in a short amount of time. This is more cost and energy effective than constantly keeping the B2O heating/cooling loop at a pre-defined temperature.

The key to optimization is by allowing the B2O to reach it's lowest tolerance in setpoint temperature, then by supplying energy to the system in a short time frame. Before optimization can be met however, the modeling of the setpoint temperature of the B2O needs to be complete and understood. However, a definition of optimization is in place for further progress on this project.

Methods and Approach: Thermodynamic Modeling

The methods used to model the energy consumption involve deploying the conservation of energy laws around the B2O system, also known as energy balances.

After all energy flow is included in the energy balance model, a relationship between the mechanically controlled valves and the temperature supply can be established. This relationship can be established by observing the change in flow rate (dictated by the valve opening) to the B2O setpoint temperature.

The future goal is to then provide the operators at Biosphere 2 with a clear decisive model, whether in the form of Excel or a MATLAB program, which will dictate the appropriate heating/cooling loop temperatures along with the valve positions depending on the time of day and the time of year.

This method was chosen because sufficient data is given for the heat exchanger and B2O such as temperature, flow rate, heating/cooling capacity, steady state conditions, schematics, geometric dimensions, and process flow diagrams, and because the laws of thermodynamics are well-understood in a simple balance. With large amounts of data, less explicit calculations are completed and instead, trends and patterns will take place between data sets that will assist in the modeling.

For simplicity, the initial energy balance was drawn around the HX-1, denoted by Figure 2 below, which created a basic model of the heat exchanger flow of energy. In the future, once the energy demand of the HX-1 balance is modeled and understood, the energy balance can be extended to include the boiler and the chiller, and eventually include the B2O and atmospheric heat interactions.

The energy carried by the supply water to HX-1, $Q_{HX1,sup}$, is one of several important numbers that will be explicitly calculated. If the energy of the incoming water to HX-1 is known, then other factors affecting this can be explored, such as the energy contained in the water needed from the boiler or chiller.

Figure 2 displays the energy flow around the heat exchanger (the same heat exchanger from Figure 1).

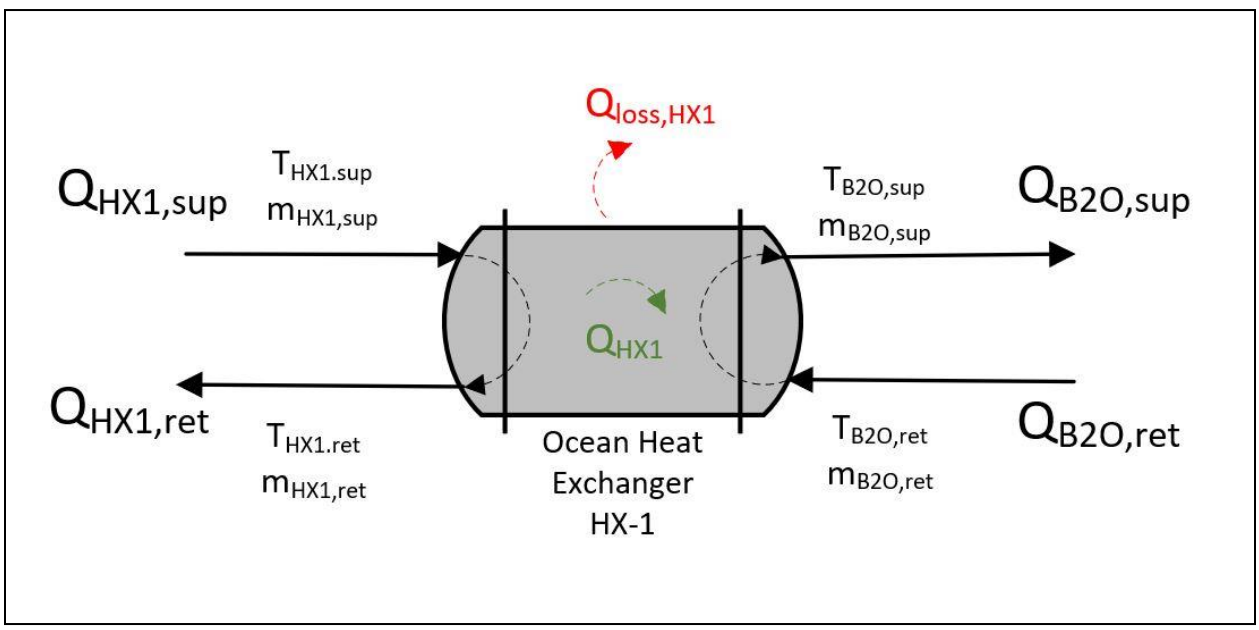


Figure 2: Schematic of HX-1 from B2O

In this schematic, $Q_i$corresponds to the energy contained in each stream, T_i corresponds to the temperature of each stream, and m_i corresponds to the flowrate of each stream.

The transfer of heat between the separated water in the heat exchanger follows the second law of thermodynamics in which energy from one heated stream of water is transferred to the cooler stream of water. This relationship is captured by the Heat transfer rate, Equation 2.

$$Q = UA\Delta T \tag{2}$$

Where Q is the heat transfer rate, U is the overall heat transfer coefficient, A is the effective heat transfer area, and ΔT is the mean temperature difference.

Since energy is conserved, it is known that the energy entering the system must be equal to the energy leaving the system.

$$Q_{in} = Q_{out} \tag{3}$$

Drawing the energy balance around the B2O system, (3) becomes

$$Q_{HX1,sup} + Q_{B2O,ret} = Q_{B2O,sup} + Q_{HX1,ret} + Q_{loss,B2O} + Q_{loss,HX1} \tag{4}$$

where the losses in the B2O are:

$$Q_{loss,B2O} = Q_{evap,B2O} + Q_{rad,B2O} + Q_{wall,B2O} \tag{5}$$

The losses from the heat exchanger, $Q_{loss,HX1}$, are a function of heat exchanger efficiency and will not be mathematically modeled.

Initially, we will ignore the B2O losses and focus on the simple system

$$Q_{HX1,sup} + Q_{B2O,ret} = Q_{B2O,sup} + Q_{HX1,ret}$$

Since we are interested in the energy of the HX-1 supply, $Q_{HX1,sup}$ is isolated.

$$Q_{HX1,sup} = Q_{B2O,sup} + Q_{HX1,ret} - Q_{B2O,ret} \tag{4}$$

For a heat exchanger, it is known that (2) becomes

$$Q_i = m_i C_{pi}(T_i - T_R) \tag{5}$$

Where m_i is the mass flowrate, C_{pi} is the specific heat of the liquid, and T_i, T_R are temperatures. T_R is an intermediate temperature in the heat exchanger, and is not known.

Combining (4) and (5), and assuming open-loop heating/cooling,

$$Q_{HX1,sup} = m_{B2O,sup}C_{p,water}\left(T_{B2O,sup} - T_R\right) + m_{HX1,ret}C_{p,water}\left(T_{HX1,ret} - T_R\right) \\ -m_{B2O,ret}C_{p,water}\left(T_{B2O,ret} - T_R\right) \tag{6}$$

Since the water is the only liquid transferring heat in HX-1, the specific heat $C_{p,water}$ is constant and can be factored out.

$$Q_{HX1,sup} = C_{p,water}\left[m_{B2O,sup}\left(T_{B2O,sup} - T_R\right) + m_{HX1,ret}\left(T_{HX1,ret} - T_R\right) - m_{B2O,ret}\left(T_{B2O,ret} - T_R\right)\right] \quad (7)$$

(7) models the energy of the HX-1 supply temperature and depends on the temperatures of the other streams as well as their mass flowrates.

Since the volume of B2O is constant and the rate at which water entering B2O equals the rate at which water exits B2O, $m_{B2O,sup} = m_{B2O,ret}$.

$$Q_{HX1,sup} = C_{p,water}[m_{B2O,sup}\left(T_{B2O,sup} - T_{B2O,ret}\right) + m_{HX1,ret}\left(T_{HX1,ret} - T_R\right)]$$

By expanding the left-hand side using (5) again and by assuming that HX-1 has a constant volume of water in it at all times, this forces $m_{HX1,ret} = m_{HX1,sup}$:

$$m_{HX1,sup}C_{p,water}(T_{HX1,sup} - T_R) = C_{p,water}[m_{B2O,sup}\left(T_{B2O,sup} - T_{B2O,ret}\right) + m_{HX1,ret}\left(T_{HX1,ret} - T_R\right)]$$

Rearranging,

$$T_{HX1,sup} = \frac{m_{B2O,sup}}{m_{HX1,sup}}\left(T_{B2O,sup} - T_{B2O,ret}\right) + T_{HX1,ret} \quad (8)$$

Given by (8), now there is an energy balance derivation that relates the incoming HX-1 water temperature to the temperatures of the other streams as well as their mass flow rates. Using (8), the incoming energy to HX-1, $Q_{HX1,sup}$, can be determined to help model how much energy HX-1 is using.

With Excel data provided by the Biosphere 2 SCADA data center, the variables $T_{HX1,sup}$, $T_{B2O,sup}$, $T_{HX1,ret}$, $T_{B2O,ret}$, $m_{B2O,sup}$, and $m_{HX1,sup}$ are all known. These variables change throughout the time of day, and the data for each variable was collected every 15 minutes from September 27th, 2019 to March 6th, 2020. The data comes from the temperature sensors and flowrate sensors included in Figure 2.

The large amount of data was collected and implemented into (8) using Excel. Since $T_{HX1,sup}$ is known, it can be used as a basis of comparison when calculated for every data point corresponding to a given point in time in the data set.

Once $T_{HX1,sup}$ is calculated and corrected for heat exchanger losses, we can use (2) and (5) again to yield

$$Q_{HX1,sup,calc,corr} = m_{HX1,sup}C_{p,water}\left(T_{HX1,sup,calc,corr} - T_{HX1,ret}\right) \quad (9)$$

The corrected $T_{HX1,sup}$ that was calculated is given by

$$T_{HX1,sup,calc,corr} = T_{HX1,sup,calc} + \Delta(T_{HX1,sup,calc}, T_{HX1,sup,actual})$$

Where $\Delta(T_{HX1,sup,calc}, T_{HX1,sup,actual})$ is the average difference between the actual HX-1 supply temperature and the calculated HX-1 supply temperature.

Equation (6) will then be compared to the actual energy entering HX-1, which is given by the actual temperature entering HX-1

$$Q_{HX1,sup,actual} = m_{HX1,sup} C_{p,water} \left(T_{HX1,sup,actual} - T_{HX1,ret} \right) \tag{10}$$

For the simple energy balance around HX-1, equations (9) and (10) were graphed in Excel and compared to one another in order to establish the accuracy of the derived model. This comparison is denoted by Figure 3 in the Results section.

Methods and Approach: Machine Learning

Another way to approach this problem is by creating an autonomous controller that could be set up and used year-round to continuously optimize the system. While traditional controllers such as Partial Integral Derivative (PID) controllers are accurate, novel controller systems utilizing artificial intelligence could provide even greater gains in energy efficiency. For this project, we explored using machine learning technology, specifically an Artificial Neural Network, to create a controller that could optimize the pool heat exchanger system for energy consumption.

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{11}$$

Artificial Neural Networks are designed to approximate the layers of neurons found in the brains of many animals. As described in *Recurrent Neural Networks: Designs and Applications* by Larry Medsker and L Jane, the design includes an input layer, an output layer, and one or more “hidden” layers. These layers are made up of a series of nodes. Each node is assigned a weight, consisting of a numerical value, and each node is “connected” to every other node in the next layer as well as the previous layer. An example of this layered node design is shown in figure A. The term “hidden layers” refers to layers that are not input or output layers and cannot be directly observed while the system is running. A sigmoid function (given by equation 11), is often used to correct node outputs, keeping them between 0 and 1. This allows for the approximation of nonlinear relationships by Artificial Neural Networks, while preventing excessively large node output values that could negatively impact the networks convergence to a solution or impact computational time.

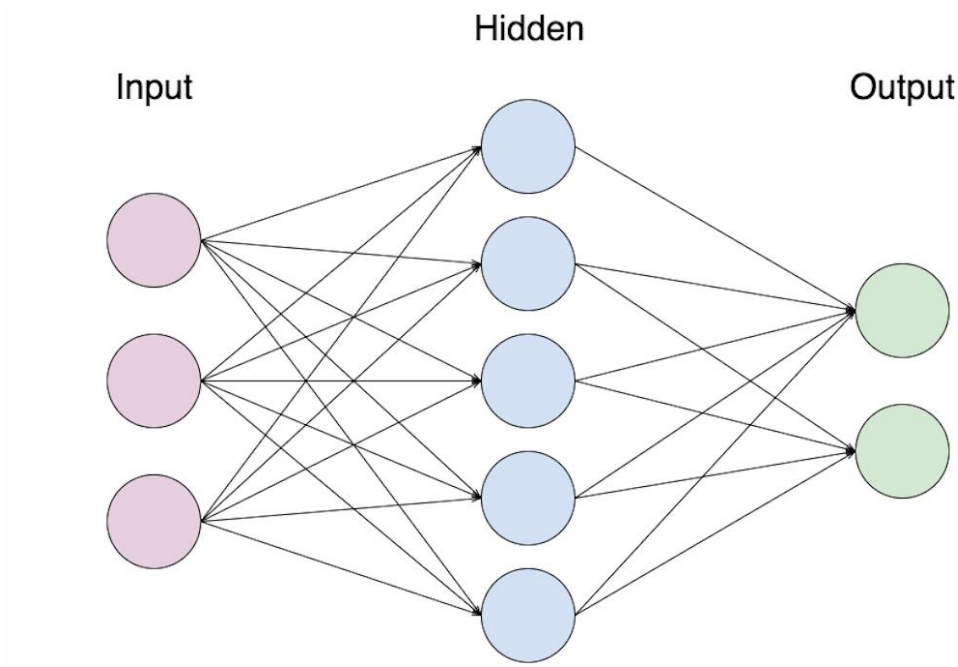


Figure 3: An example of an Artificial Neural Network with three layers

When creating our methodology, we relied heavily on a 2017 paper by Wang et al titled *A Long-Short Term Memory Recurrent Neural Network Based Reinforcement Learning Controller for Office Heating Ventilation and Air Conditioning Systems*. As the name of this paper implies, its scope is limited to office HVAC and A/C control systems. In the paper, Wang et al reported an improvement in energy efficiency of 2.5%, and in increase in thermal comfort of 15% on average. When considering application to the Biosphere 2 Ocean, thermal comfort is not a necessary factor to optimize for, because the ocean temperature is kept within tight range of a set point.

In their experiment, Wang et al made use of a Long-Short Term Memory Network (LSTM), a variation on a Recurrent Neural Network (RNN). RNNs are a type of Artificial Neural Network that can be unrolled through time, with each time step adding an additional hidden layer. While these are convenient for controller-based applications, there are problems present with this type of networks. One such problem is the vanishing/exploding gradient problem.

To train a recurrent neural network, information must be backpropagated through time to adjust the nodes of previous layers, allowing the network to incorporate new information. While explained in more depth in the paper by Wang et al, a brief summary of the math behind the exploding/vanishing gradient problem follows.

First, let $h_t = f(a_t)$ be the state at time t, given as a function of some action taken, a. If loses at a given time step are given by epsilon, then the total gradient loss gradient is given by equation 12.

$$\frac{\partial \varepsilon_t}{\partial \theta} = \sum_{1 \le t \le T} \left(\frac{\partial \varepsilon_t}{\partial h_t} \frac{\partial h_t}{\partial h_k} \frac{\partial h_k}{\partial \theta} \right) \tag{12}$$

The temporal gradient flow-back component, $\frac{\partial h_t}{\partial h_k}$, is then given by equation 13.

$$\frac{\partial h_t}{\partial h_k} = \prod_{t \geq i > k} \frac{\partial h_i}{\partial h_{i-1}} = \prod_{t \geq i > k} {W_{rec}}^T diag\big(g'(h_{i-1})\big) \tag{13}$$

Where W_{rec} is a recurring weight and T is the total number of time steps. Here we can see that for very small or very large values of W_{rec} and large values of T, the gradient will either disappear completely or become very large. To avoid this problem, Wang et al utilized Long-Short Term Neural Networks, or LSTMs, for their reinforcement learning controller.

As opposed to a traditional RNN, where multiple layers are unrolled through time, an LSTM is composed of a predetermined set number of layers. The most significant differentiating factor found in LSTM networks is a series of gates that modulate the flow of information into, and out of, the network. This includes an input gate, an output gate, and a forget gate. The input gate determines what information is allowed to update the hidden layer cell state of the LSTM, the output gate outputs information relevant to a solution at each time step, and the forget gate updates the hidden cell state by disregarding information that is no longer useful. A diagram showing the basic LSTM architecture is shown below in figure B. For more specific information on and applications of LSTMs, readers can refer to *Deep Learning* by John Kelleher or the 2019 article by Alex Sherstinsky, *Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) network*.

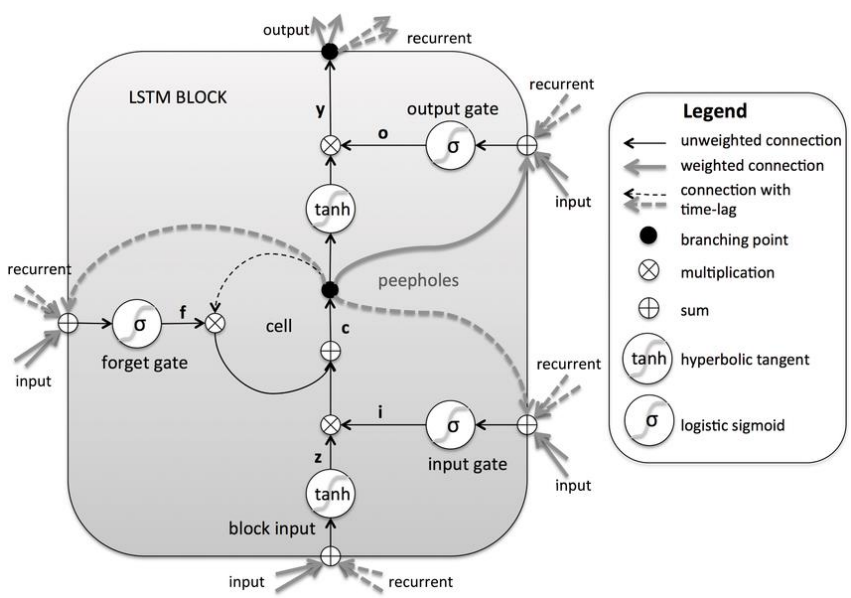


Figure 4: Top down design of an LSTM, where cell c consists of hidden layers

In the article Wang et al, an actor critic reinforced learning system was used. An example of this system is shown in figure C. In this actor critic system, both the actor and the critic are represented by LSTM networks. The system is represented by an Energy Plus simulation. At every time step, the system will

post state values to both the actor and critic, as well as provide an award for the critic. The critic will then compute some value for the actor, based off the reward received and the state of the system. The actor will use this state value in conjunction with the current state to pick a new action for the next time step. The reward received by the critic is given by way of a sum that extends from 1 to time T. The sum uses a discounting term so that subsequent rewards will have less impact on future decisions made by the system.

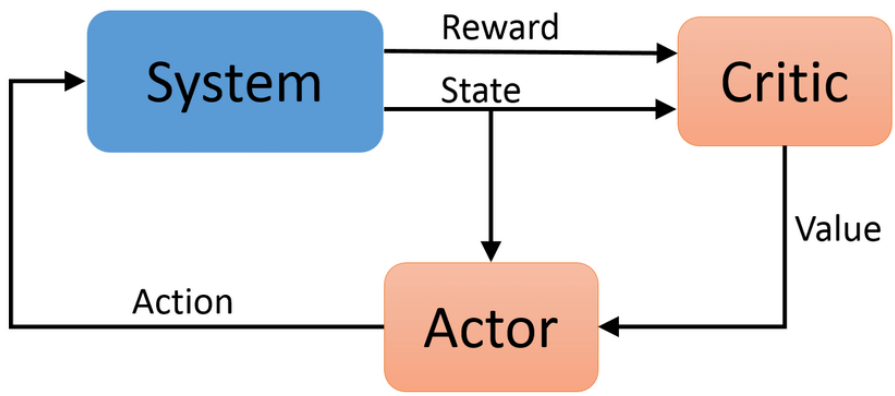


Figure 5: Flow chart of the actor critic system

For our project we began by constructing a basic LSTM using MATLAB's deep learning toolbox. This network consisted of an input layer, an LSTM layer, a fully connected layer, a SoftMax layer, and a classification output layer. The SoftMax layer uses a SoftMax function as the output unit activation function. The SoftMax layer, as described by MATLAB documentation, is described by equation 4. We then collated roughly a week of B2O data into a 10x1000 matrix that could be used to provide inputs to the network for 1000 time steps, roughly equivalent to 10 days worth of B2O data. The inputs selected were B2O pool temperature, energy usage in KW, and both ocean and heat exchanger supply and return temperatures and pressures. We then created an output vector, organized as an array of heat exchanger supply temperatures ranging from 85 to 140 degrees F. With the collated data acting as an input, the network was intended to select a value from the output array at every time step.

$$y_r(x) = \frac{\exp\left(a_r(x)\right)}{\sum_{j=1}^{k} \exp\left(a_j(x)\right)}, where\ 0 \leq y_t \leq 1\ and \sum_{j=1}^{k} y_j = 1 \tag{14}$$

Results: Thermodynamic Modeling

Since the data set is very large in that measurements were recorded every 15 minutes between September 27th, 2019 to March 6th, 2020, a small portion of data was first used to understand and model the HX-1 system for a one-month timeline.

The timeframe for which data was initially used was selected for January 1st, 2020 to January 23rd, 2020. During this window, the B2O needed to be heated during the winter and the boiler was being used.

The graphical comparison of equations (9) and (10) are denoted below in Figure 6.

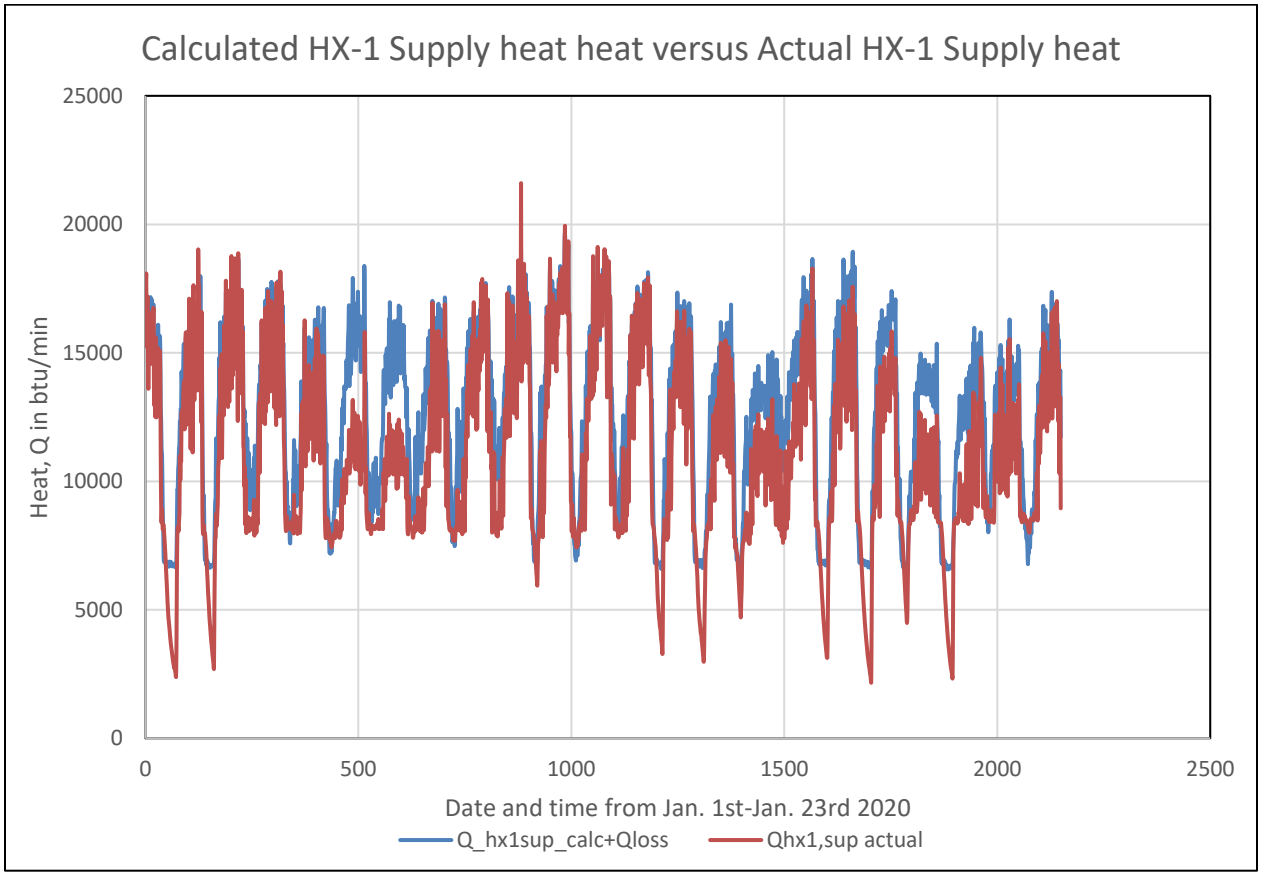


Figure 6: HX-1 Supply Energy comparison, calculated and actual

As a result, the energy balance derivation matches the trend of actual data with an included averaged correction factor in the temperature. This is an indication that the derivation was successful in exhibiting the heat exchange relationship in the system, and successfully models the laws of thermodynamics that takes place in the system. On the y-axis is the energy in $\frac{btu}{min}$, and on the x-axis is the time of day.

The oscillatory behavior is given by the rising and falling temperature of the B2O setpoint depending on the time of the day. As the day progresses and sunlight is visible, the B2O requires less energy to be heated, in which the oscillations are at a minima. As the day ends and the sunlight is no longer visible during the night, the B2O requires more energy to remain heated at its setpoint temperature, in which the oscillations are at a maxima. This oscillatory behavior can be further understood as the model is

refined in the future, in which the temperature and time of day can be included in the model. For now, the matching oscillations indicate a correct modeling of the thermodynamic responses in the system.

Essentially, the calculated and measured HX-1 water supply energy follows the same shape and trend but has apparent differences at the maxima and minima. The differences in the minima and maxima are a result of unaccounted losses in the system during certain temperature extremes. For example, when $Q_{HX1,sup,actual}$ was higher than $Q_{HX1,sup,calc,corr}$ in the middle of the day, this indicates that there is energy loss that was not included in the derivation; during the middle of the day, water can evaporate from the surrounding hot atmospheric air. This would make $Q_{HX1,sup,actual}$ higher in that, more energy needs to be added to B2O to keep it cool during the middle of the day to offset the effects of the hot air outside, in which the derivation model does not capture. These unaccounted losses are solidified in the symmetric occurrences at every peak of the maxima and minima.

The energy losses depending on the time of day is denoted by Figure 7 below.

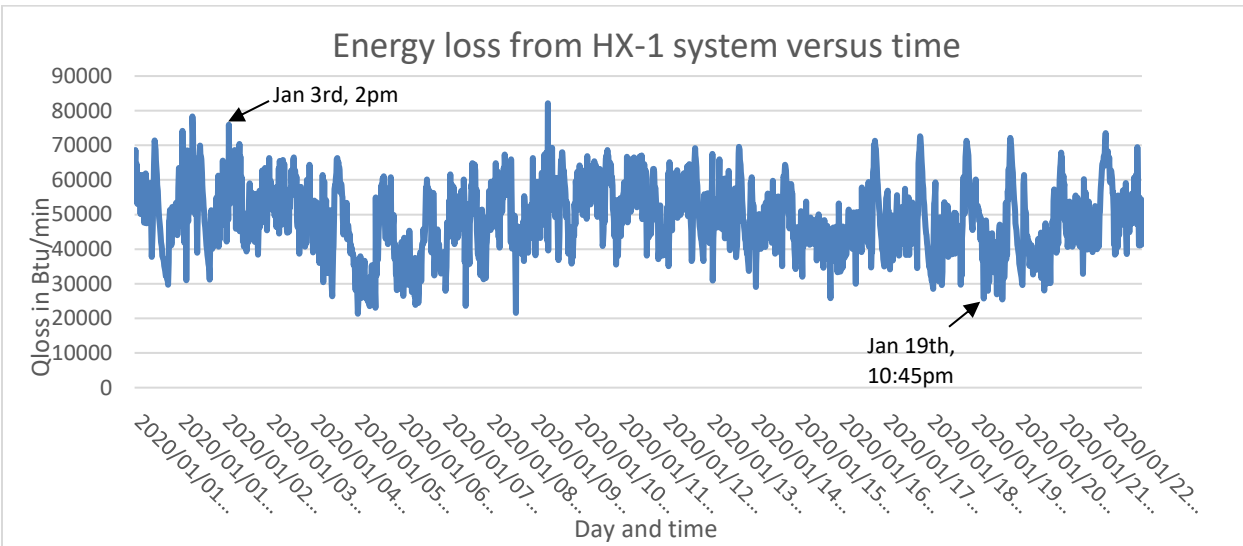


Figure 7: Energy loss in the HX-1 system versus time of day

This graph indicates that ambient air temperature surrounding the B2O and other weather conditions have a large role in the system. As the day goes on between January 1st and January 23rd, the temperature of the environment in Tucson increases, possibly from increased water evaporation or effects of solar radiation. As an example, a large energy loss spike can be seen in the middle of the day on January 3rd, and a minimum energy loss can be seen late at night on January 19th.

In the calculated HX-1 supply temperature, assumptions were made under a closed system, in which the time of day and ambient conditions were not considered. Additionally, issues such as pump failures, shutdowns, and other external factors were not considered when calculating the HX-1 supply water temperature.

While these minima and maxima exist, the matching trend demonstrates the surprising reliability and accuracy of computing the needed HX-1 supply water energy with little external factors added into the system.

The simple derived relationship was also simulated using a MATLAB GUI program, in which the user can define the incoming temperatures and the output is the HX-1 supply water mass flow rate and HX-1 supply temperature.

The interface can be viewed in Figure 8 below.

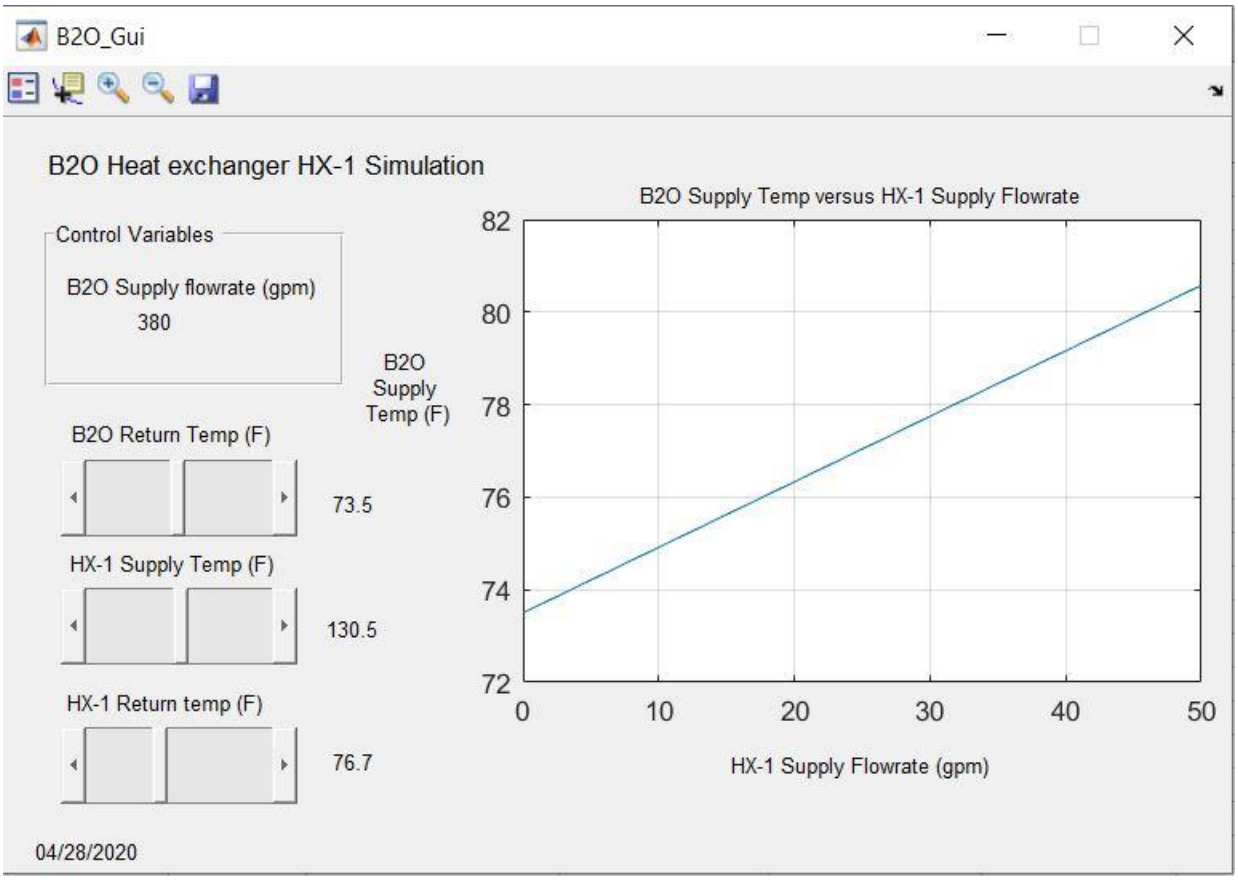


Figure 8: MATLAB GUI simulation for certain parameters throughout January.

Currently, the simulation does not accurately reflect the needed flow rate or temperatures of the B2O system, but can be refined later on in future groups. The main achievement of the simulation was laying the framework for the MATLAB code, namely how to add sliders and update the graph in real-time. Since this simulation is based off of and reflects the simple model derived, inaccuracy of the simulation reflects the accuracy of the model. In addition, large error occurs in the flow rate from the sensitivities in the temperate; just a fraction of a degree Fahrenheit can offset the needed flow rate up to 10 gpm.

Results: Machine Learning

Unfortunately, we could not produce meaningful results using the network created. There are several reasons for this. The first is that the network was set up primarily using a template for classification networks. Although in some ways the problem of creating a controller can be reduced to that of a classification problem, it is likely that custom layers would need to be created in conjunction with a deeper understanding of the intricacies of LSTM networks. The second problem we faced was that of training data. In the paper by Wang et al, a simulation of the office building in Energy Plus was used to provide feedback and training data to the network. In our case, the importance of a working

simulation was not realized until late in the semester. As a result, the only data we could use to train the network was the SCADA data provided to us by the Biosphere 2 team.

While the SCADA data provided was useful, its use in training the network was limited. This is because controllers using artificial neural networks need either a reward function in conjunction with a simulation, or an optimal output at each time step to be trained. Given nothing but data and subsequent outputs, it is possible to train a predictive network. However, a network tasked with optimization will need to either be provided with an optimal solution or allowed to explore the system discovering sub optimal solutions along the way.

Future Improvements: Thermodynamic Modeling

Using this same energy balance given by equation (4), a calculation similar to equation (9) and (10) can be used more successfully to predict the future needed supply water energies once more parameters are included in the system and once more refined corrective factors are added. As the energy balance model is refined, the relationship between B2O setpoint temperature and time of day can be further understood, and eventually, an optimization can be reached.

The actions taken by future groups assigned to this project should be completed in order to refine the model:

- Continue model for the rest of the months after January, especially summer
- Estimate or calculate energy losses: $Q_{loss,B2O} = Q_{evap,B2O} + Q_{rad,B2O} + Q_{wall,B2O}$
- Understand role of valves by communicating with operators at B2O
- Extend energy balance around entire system (there are files for temperatures leaving the boiler/chiller as well)

For the MATLAB simulation, future groups should also:

- Learn and understand GUI script writing
- Return temperatures should be removed as a slider option and should be dependent on the temperature of B2O or dependent on supply temperatures with constant Q
- Final MATLAB GUI simulation should have only heat or temperature of HX-1 supply as the slider
- Add disturbances

Once the supply temperature relationship to the heating/cooling demand is modeled accurately, the relationship between the mechanical valve opening and the supply temperature can be understood and a relationship between the B2O setpoint temperature and the valve-opening will be established and optimized. Then, this can be included in the MATLAB GUI simulation as a possible interface for the operators at Biosphere 2 to use.

Conclusions and Future Goals

The basic conclusions of the project are as follows:

- An estimation model was developed from thermodynamics
- Framework for project is solidified for future groups

- Optimization can be achieved through refining model and the MATLAB GUI program by adding disturbances

Ideally, maximizing the temperature difference between the B2O setpoint temperature and the B2O incoming supply water will result in increased energy efficiency and reduced operating costs. This is because the larger the temperature gradient between two systems, the faster the net heat flow occurs, which results in less metered energy usage for cost.

Overall, the derived thermodynamic match the measured data from the Biosphere 2 SCADA data center for the month of January. While there is some error in the magnitude of the minima, the calculated model is an averaged scalar value away from matching the measured data. With a more accurate way of adding a corrective factor, the model can be even more accurate and can be extended to additional months.

What has been accomplished so far includes analyzing advanced Piping and Instrumentation Diagrams (P&ID), making sense of an enormous data sets for dozens of Excel files, organizing large amounts of sensor data, understanding the mechanisms by which B2O is heated/cooled, and familiarizing with each schematic provided by Biosphere 2. In each schematic, there multiple codes, valves, pumps, dimensions, piping, and streams. The pathways of the boiler/chiller to the heat exchanger to the B2O and back was difficult to decipher as well.

The thermodynamic laws that a heat exchanger follows was also not immediately intuitive, and research on the simple modeling of a heat exchanger was accomplished. Knowing which variables were provided and what variable to look for was not obvious but were understood over time.

The most difficult task was understanding the schematics; mapping physical locations to a specific Excel file was the greatest accomplishment. Using logic of heat transfer and tedious iterations, each Excel file was mapped to a specific sensor or water line.

Finding an approach to the problem also took a large amount of time; uncertainties of where to draw an energy balance around and over-ambition delayed the analysis. At first, the goal was to analyze all the data at once for all scenarios. Once the problem was broken down into simpler steps with a realistic goal, analysis became possible and a successful analysis of data was performed for a one-month time frame.

For future groups, time and attention should be diverted to analyzing the rest of the data and relating these to the manual supply valves. Another strong future goal to consider is to understand and develop a model for the varying time of year; in the summer, large cooling demands may reach extremes, and during cold winters, large heating demands may also reach extremes. This is due to atmosphere heat exchange with the B2O and other streams of water and changing seasons. Correlating the time of year to the B2O setpoint temperature will become a future essential relationship for a complete Biosphere 2 ocean heat exchange optimization.

In regard to the machine learning, although limited training data was a large constraint in the ability to create a working controller, a modified solution may be available. Using the MATLAB GUI Simulation created for the optimization aspect of the project (mentioned above), it could be possible to train an artificial network using the optimal outputs at each timestep from the thermodynamic analysis of the system. This method does have its own constraints; the neural network will only be able to converge on

a solution as accurate as the simulation provides, and training data is limited. However, in lieu of an accurate simulation, this could be used render a network or a series of networks realizable, providing proof of concept. As mentioned in the future goals, as the optimization model is improved and expanded upon, it could be used in conjunction with the machine learning method, which would in turn help the machine learning program choose the best output after given input data.

Ultimately, a simulation incorporating weather data, as well as B2O and heat exchanger temperature, inputs, and outputs would be needed to create and train a self-sufficient reinforcement learning controller. Such a controller, once created, could be left to run the B2O with limited human oversight, providing consistent energy savings year-round.

Acknowledgments

This project was mentored by Samuel McLaren, University of Arizona, whose help is acknowledged with great appreciation. In addition, the help and resources from the faculty of Biosphere 2, namely John Adams, Deputy Director, and Wei-Ren Ng, Electrical Engineer is greatly appreciated. The modeling assistance from Dr. Songtao Xie, The University of Arizona, is also greatly appreciated.

References

1. Biome Point List[1], .xls file. Provided by John Adams at Biosphere 2.
2. Biosphere 2 Energy Center Diagram. Provided by John Adams at Biosphere 2.
3. Biosphere 2 Ocean Tank Renovation. Ocean Tank Renovation – Piping and Instrumentation Diagram. Sheets LSO.41, LSO.45. Provided by John Adams at Biosphere 2.
4. Dacombe, James. "An Introduction to Artificial Neural Networks (with Example)." *Medium*, Medium, 23 Oct. 2017, medium.com/@jamesdacombe/an-introduction-to-artificial-neural-networks-with-example-ad459bb6941b.
5. Energy Center Points List[1], .xlsx file. Provided by John Adams at Biosphere 2.
6. Fogler, H. Scott., and Gürmen M. Nihat. *Elements of Chemical Reaction Engineering*. PHI, 2013.
7. https://biosphere2.org/content/biosphere2-scada-data. Provided by John Adams at Biosphere 2.
8. Kelleher, John D. *Deep Learning*. MIT Press, 2019.
9. Language Identification in Short Utterances Using Long Short-Term Memory (LSTM) Recurrent Neural Networks - Scientific Figure on ResearchGate. Available from: https://www.researchgate.net/figure/Long-Short-Term-Memory-recurrent-neural-network-architecture-A-single-memory-block-is_fig8_292303547 [accessed 30 Apr, 2020]
10. Levenspiel, Octave. *Engineering Flow and Heat Exchange*. Springer US, 2014.
11. Medsker, Larry R., and L. C. Jain. *Recurrent Neural Networks: Design and Applications*. 1st ed., CRC Press, 2000.
12. Seborg, D. E., et al. *Process Dynamics and Control*. Wiley, 2004.
13. Sherstinsky, Alex. "Fundamentals of Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM) Network." *Physica D: Nonlinear Phenomena*, vol. 404, 2020, p. 132306., doi:10.1016/j.physd.2019.132306.
14. Team, SuperDataScience. "Recurrent Neural Networks (RNN) - The Vanishing Gradient Problem." *SuperDataScience*, 22 Aug. 2018, www.superdatascience.com/blogs/recurrent-neural-networks-rnn-the-vanishing-gradient-problem.
15. Singh, Satinder, et al. "Advances in Neural Information Processing Systems 12." MIT Press, *Policy Gradient Methods for Reinforcement Learning with Function Approximation*, 2000, pp. 1057–1063.
16. The University Of Arizona Biosphere 2 Landscape Evolution Observatory. Project Number 11-9057. June 30, 2011. Provided by John Adams at Biosphere 2.
17. University of Arizona Biosphere 2 Ocean Renovation – Heat Exchanger Package. Mechanical Controls, Sequence of Operations and Points List. Sheet Number MI001. M3PN 180158.502. Provided by John Adams at Biosphere 2.
18. Wang, Y.; Velswamy, K.; Huang, B. A Long-Short Term Memory Recurrent Neural Network *Based Reinforcement Learning Controller for Office Heating Ventilation and Air Conditioning Systems*. Processes 2017, 5, 46
19. Yang, K. (July 9, 2008). "Artificial Neural Networks (ANNs): A New Paradigm for Thermal Science and Engineering." ASME. *J. Heat Transfer*. September 2008; 130(9): 093001.https://doi.org/10.1115 /1.2944238
20. Zuccari, F, et al. "Energy Analysis of Swimming Pools for Sports Activities: Cost Effective Solutions for Efficiency Improvement." *Energy Procedia*, vol. 126, 2017, pp. 123–130., doi:10.1016/j.egypro.2017.08.131.