MECENG 249 Project 4 Report

Implementation of Machine Learning in Solar Thermal Power and Electronics Cooling

Submitted By:

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I. Introduction

A simplified yet intelligent model that teaches computers to process the data like a human brain is coined as a neural network. There are three types of neural networks namely, Artificial Neural Networks (ANN) Convolution Neural Networks (CNN), and Recurrent Neural Networks (RNN). In this project, the implementation and understanding of a simple artificial neural network is conducted. An Artificial neural network is a model with connected input/output layers and hidden layers with neurons to simulate a human brain. These models are widely used in the energy sector to evaluate systems where physical prototyping and evaluation for various operating conditions are not feasible.

In this project, the design of a boiler for converting the captured incident sun rays by an array of heliostats into electricity is considered. The design is modeled similarly to the one used in the PS10 solar thermal plant 15km west of Seville, Spain. The principle is simple the heliostats(here 624 in number with each one having an area of 121m^2) on the field capture the sun rays and reflect them onto the solar receiver(55MW nominal design intensity) where the water flowing inside the cylindrical tubes are heated. The steam generated in this steam drum is then passed into a turbine where the heat is converted into electricity via a generator. Then this steam is passed through a condenser and the cycle repeats. This is shown in figure 1.

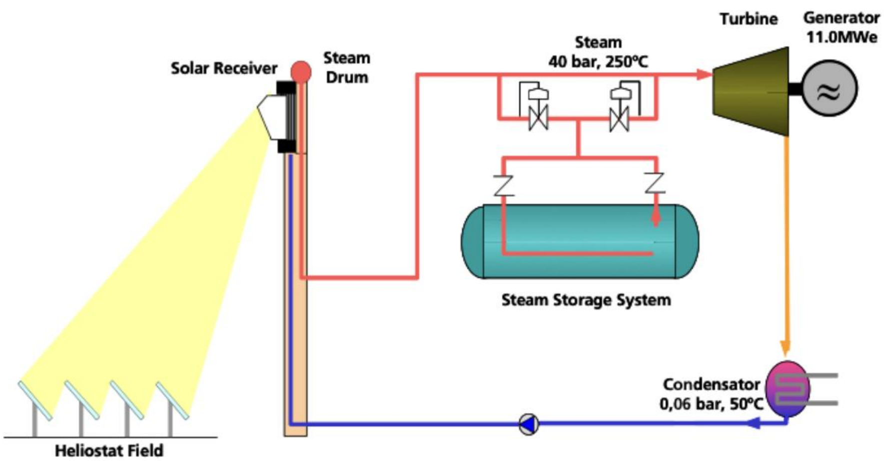


Figure 1: Representation of boiler mechanism used to generate steam to in turn generate electricity.

In the first part of the project, the system performance is evaluated by considering various parameters like the exit quality, maximum tube wall temperature, and water mass flow rate at various times. This is performed using a neural network built to predict these performance parameters for different outputs.

For the second part, an algorithm(FTCS) to determine the maximum wall temperature of a wall that is undergoing a natural convection heat transfer as shown in figure 2 below is evaluated. Using a neural network this objective is achieved.

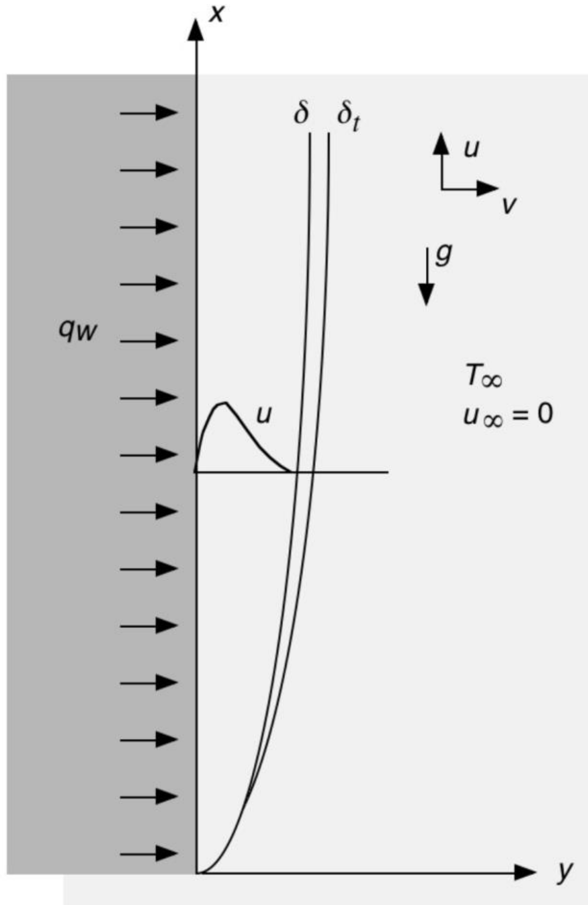


Figure 2: Representation of natural convection boundary layer flow of a heated surface in still air.

II. Nomenclature

D_i (m) Tube Inside Diameter

q''_o (W/m^2) Incident Solar flux

$\dot{m}$ (kg/s) Water Mass Flow Rate

x_e Exit Quality

$T_{w,max}$ (C) Maximum Tube Wall Temperature

III. Part One

This part of the project is focused on understanding the operating parameters and implementation of machine learning models to model a boiler like design that is used in the PS10 solar thermal power plant in Seville, Spain.

Figure 3: PS10 Solar Thermal Power Plant

For the purpose of modeling this system, a neural network model is developed and trained using the operating parameters and outputs provided in numerous data sets representing the flow boiling of water in a vertical tube at a design saturation pressure of 4.0 MPa.

1. **Task 1.1**

   This task aims to model and train an artificial neural network that is composed of three hidden layers. This is done by using a provided data set containing 3 input parameters and 2 output parameters that are to be adjusted prior to placing it within the model.

   a. Specified operating input parameters within a data file that are to be used in training an artificial neural network were uploaded within a script. In this script, a function is used to determine the median of each operating parameter. In doing so, the data is then normalized by dividing each parameter by its corresponding median value.

   b. With the provided data set being normalized, it is then separated into two different data sets consisting of a training set and a validation set. This breakdown was split with 3/4ths of data comprising the training set and the remainder being used in the validation set.

c. This task also made use of a skeleton script that is to be altered throughout the entirety of the project. Within this task, the previously altered data set was then placed within the skeleton script that utilized a keras.sequential network. This network has a Random Uniform initializer, an inlet layer with 6 neurons with an elu activation function, input_shape=[3], 3 hidden layers with 8, 16, and 8 neurons, and an outlet layer with 2 neurons with no activation function. Also, the network utilized a RMSprop optimizer and used the model.fit routine.

d. The model then went through 1734 epochs with a learning rate of 0.02 to obtain a mean absolute error of 0.023603316 which is below the required threshold of 0.025.

e. In order to compare the trained model predictions to the training data set, a log-log plot of the predicted and data value of the exit quality is found below. This model showed a mean absolute error for the fit of 0.0564545613.

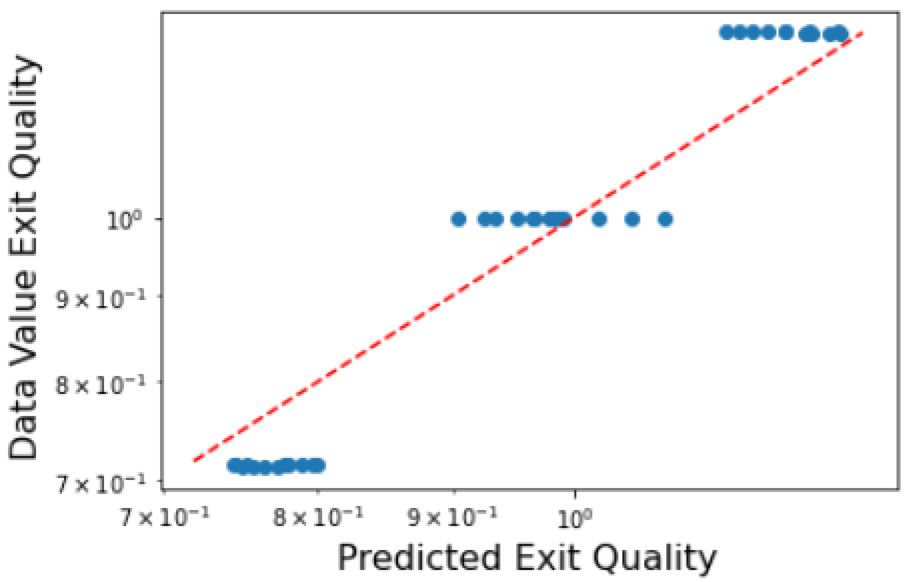


Figure 4: Log-Log plot of predicted vs training

The same is then repeated for the maximum wall temperature predicted and data values which resulted in a mean absolute error of 0.0147846.

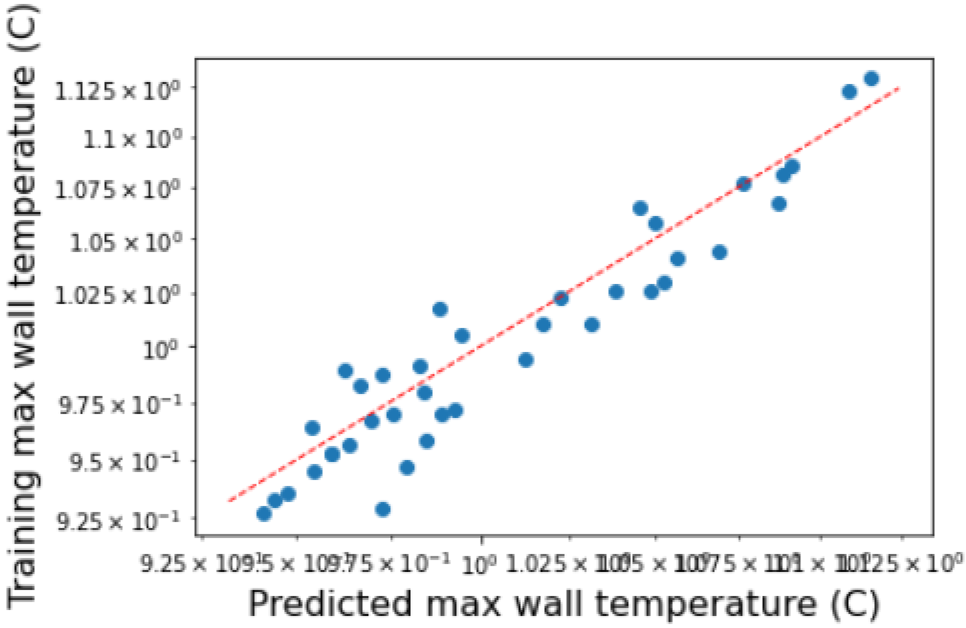


Figure 3: Log-Log plot of predicted vs training

f. The previous step is then repeated with the validation to determine if the model is overfit or underfit. For the exit quality, the mean absolute error is found to be 0.0702409554.

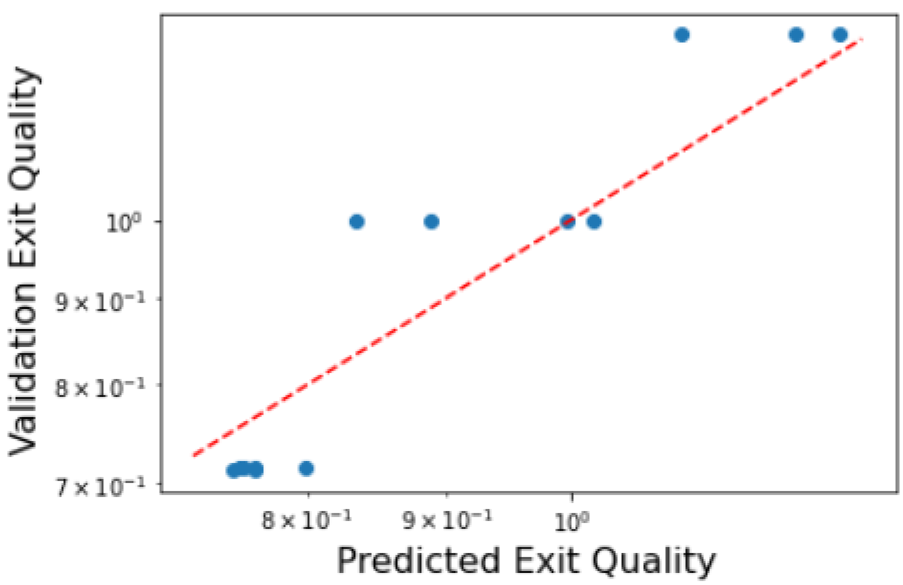


Figure 5: Log-Log plot of predicted vs training

For the maximum wall temperature, the mean absolute error is 0.01352913559.

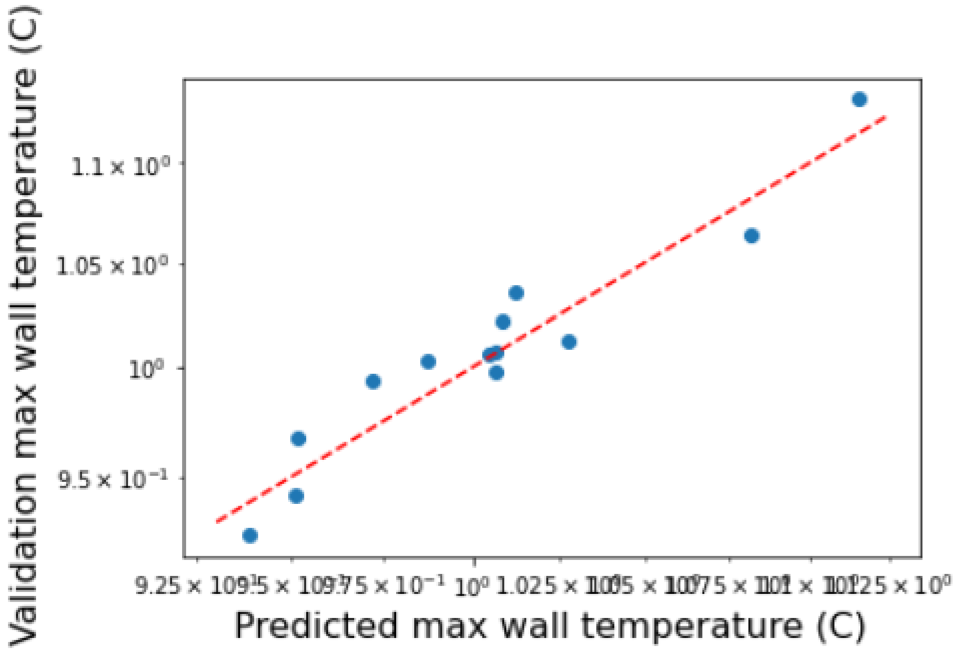


Figure 6:Log-Log plot of predicted vs validation

In completing this part of task 1.1 it is determined that the model is overfitting because the mean absolute error of the validation set is slightly higher than the training mean absolute error.

g. In further testing the model, two surface plots are created to show the outputs of exit quality and the maximum wall temperature, given a range of set operating conditions that are fed into the model. The heat flux is fixed to 750 kW/m^2, the tube inside diameter range is between 7 and 13 millimeters, and the water mass flow rate range is set between 0.05 and 0.15 kg/s.

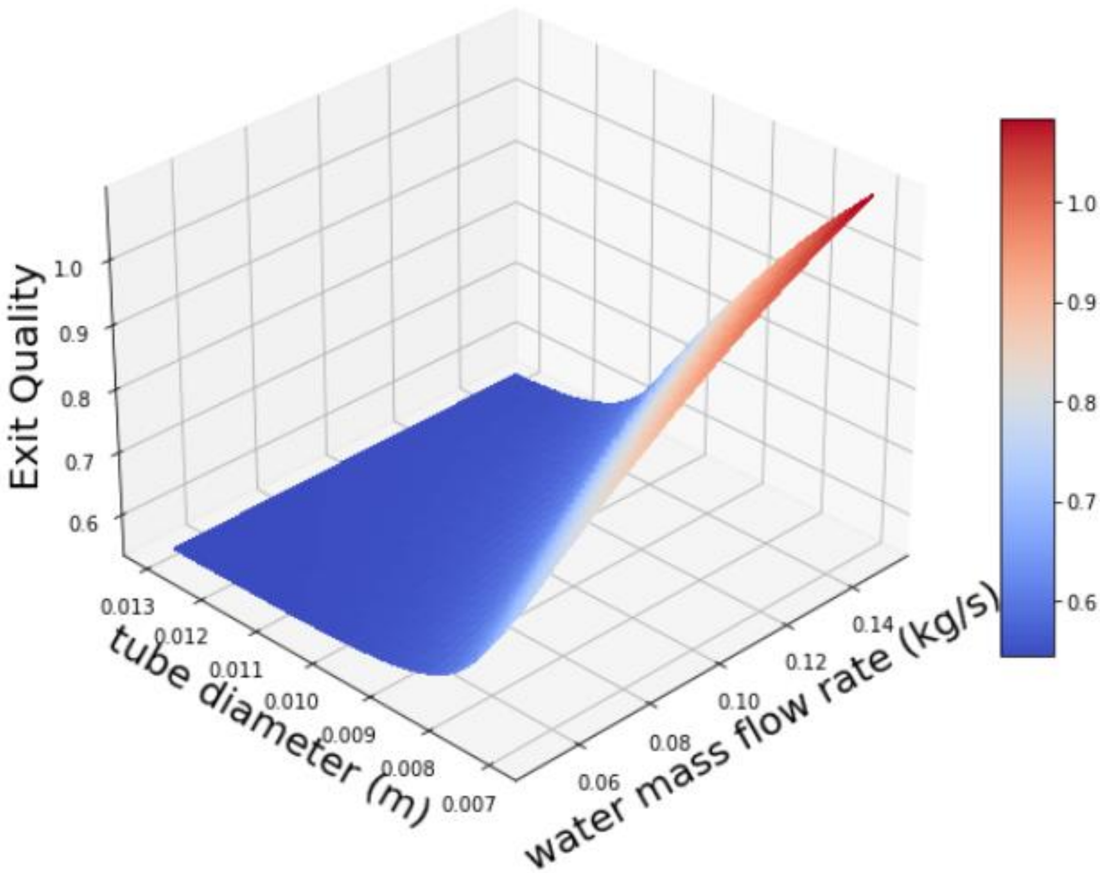


Figure 6: Surface Plot of tube diameter vs water mass flow rate vs exit quality

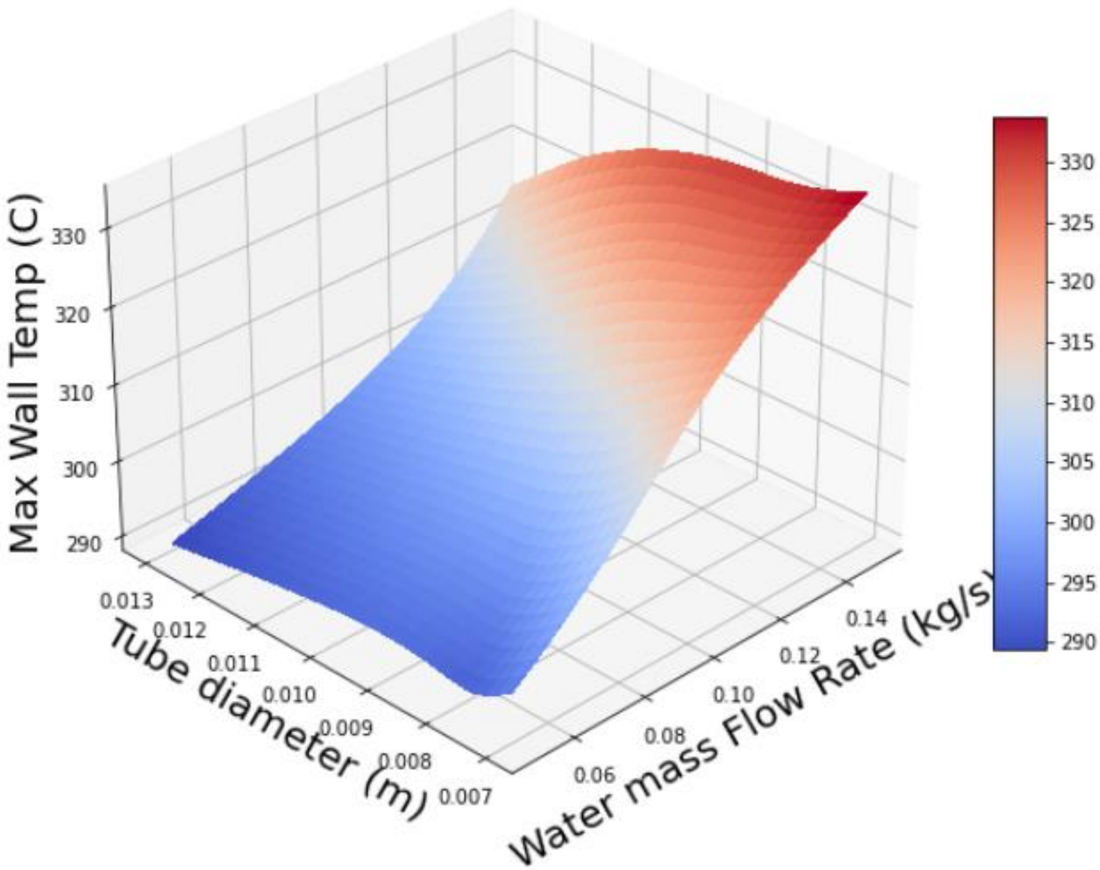


Figure 7: Surface Plot of tube diameter vs water mass flow rate vs maximum wall temperature

In creating these surface plots it can be determined that in order to achieve an output quality of about 0.75 and a maximum wall temperature that is no more than about 310°C, the tube diameter could be 8 mm with a water mass flow rate of 0.09 kg/s.

2. **Task 1.2**

   The model obtained in task 1.2 is modified with an added hidden layer with 12 neurons making it a total of 4 hidden layers with 8, 12, 16, and 8 neurons respectively. A dropout layer is added after each hidden layer with a value of 0.25 for the dropout layer argument. The model is then trained with the same data set as done earlier to achieve a low loss.

   The loss obtained after training the data is 0.02258329 in 2127 epochs with a learning rate that decreased in numerous increments from 0.02 to 0.0001. After this, the model is used to predict the exit quality and the maximum wall temperature and compared to the training dataset. The mean absolute error of this comparison is obtained as 0.02409822621 for the exit quality and

0.012044916 for the maximum wall temperature. Finally, a log-log plot of the predicted vs training data is plotted as shown below.

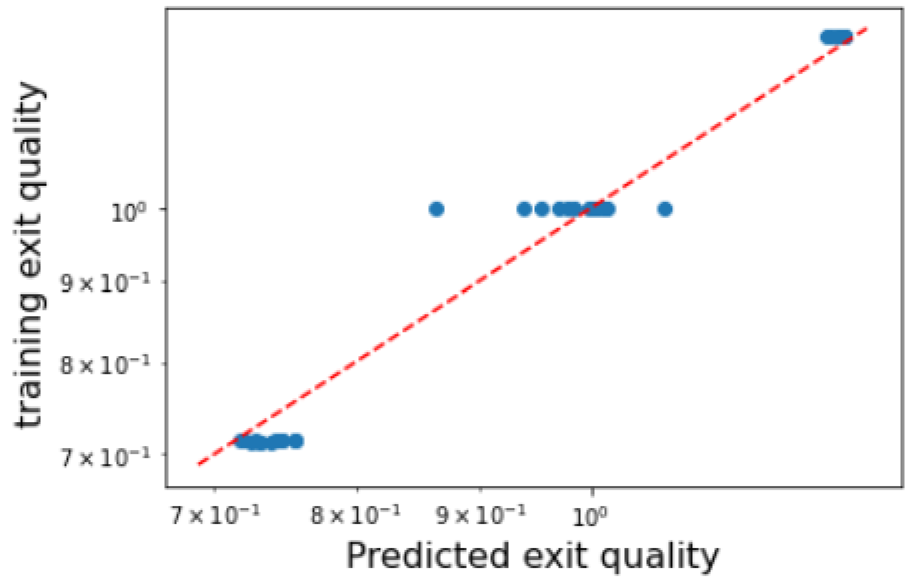


Figure 8: Log-Log plot of predicted vs training

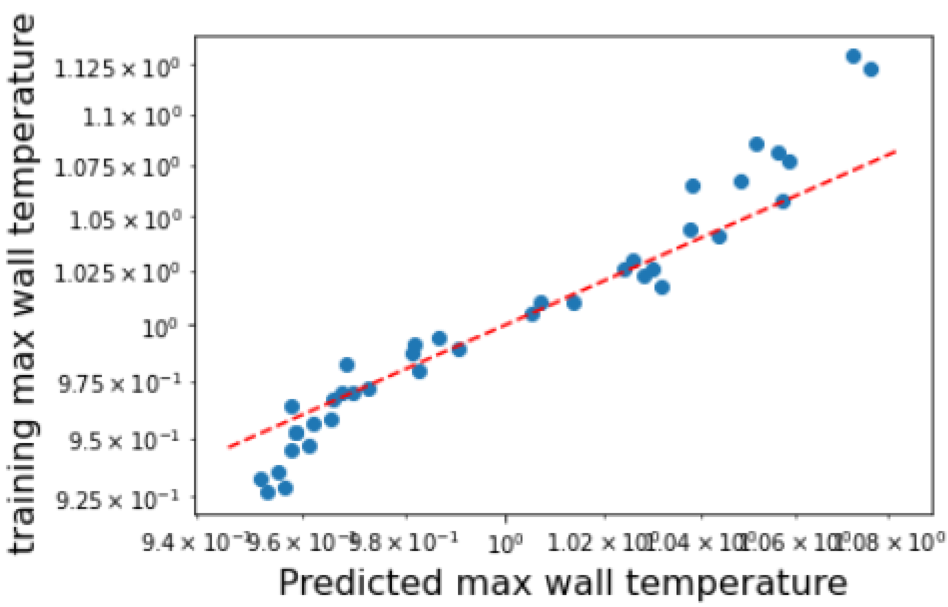


Figure 9: Log-Log plot of predicted vs validation

The same is repeated with the validation data set. The mean absolute error was obtained to be 0.04919021 for the exit quality and 0.01423145 for the maximum wall temperature. The logarithmic plots are shown below.

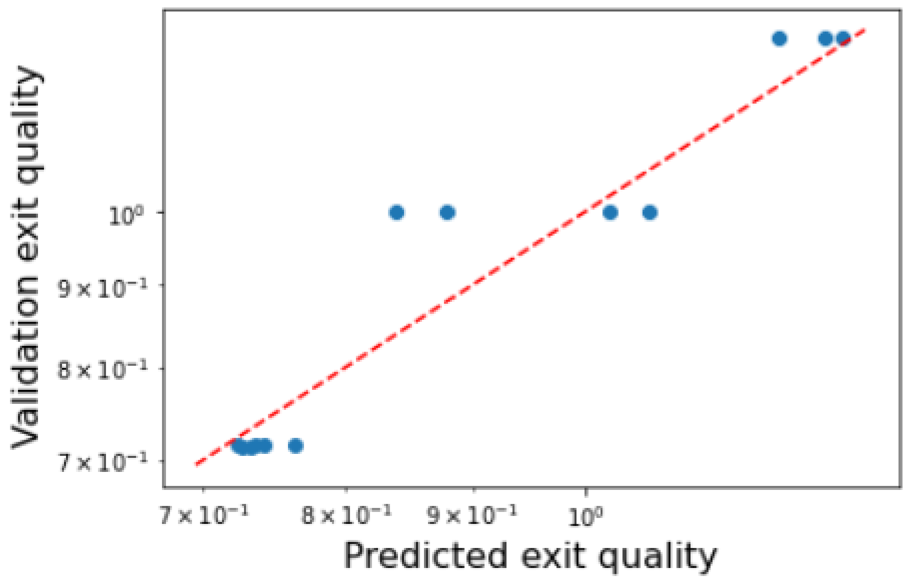


Figure 10: Log-Log plot of predicted vs training

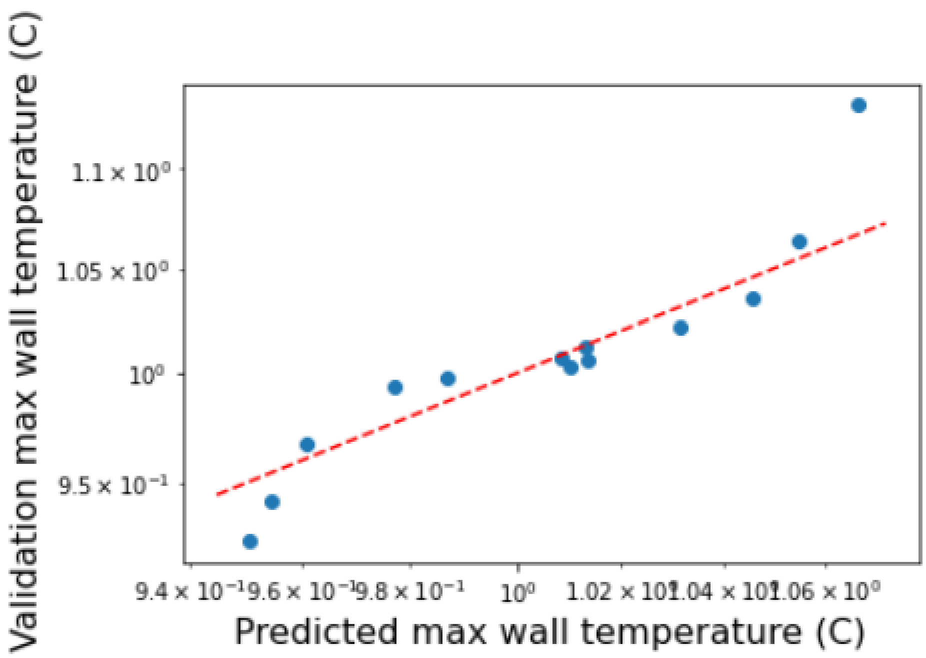


Figure 11: Log-Log plot of predicted vs validation

A surface plot is also plotted as done with the earlier model to analyze the variation of exit quality and maximum wall temperature previously used set of operating conditions and ranges.

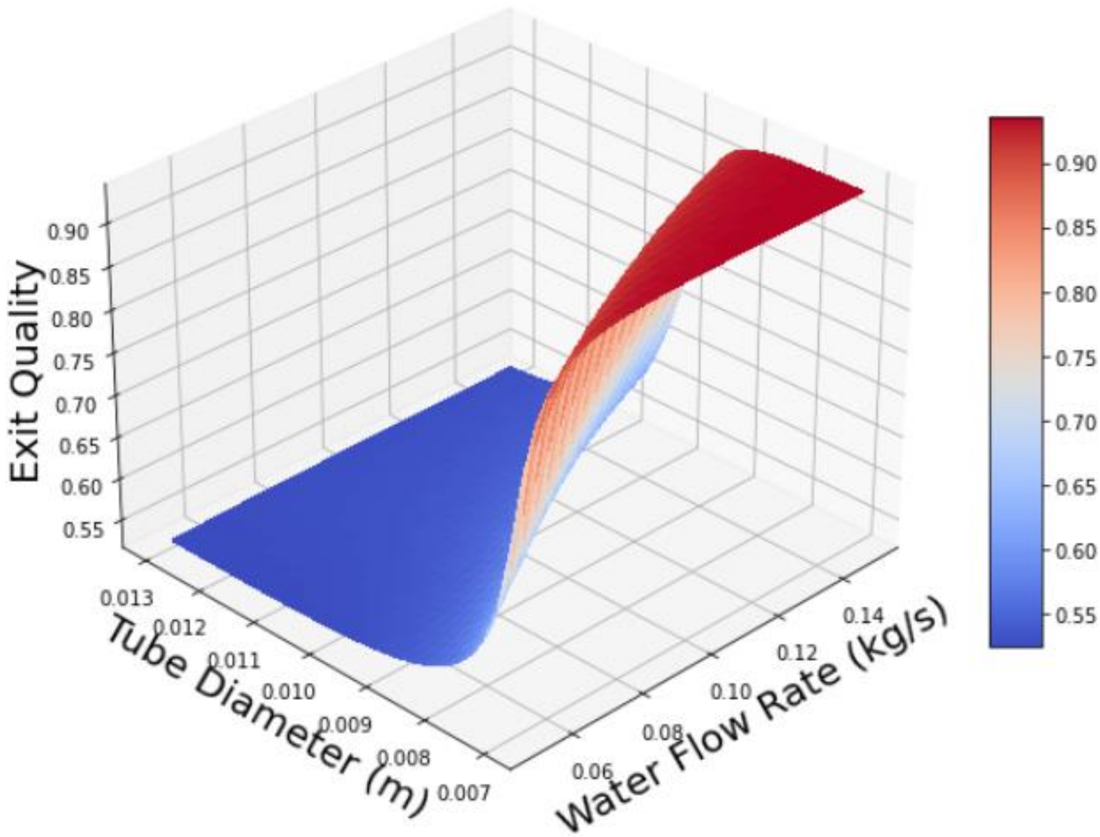


Figure 12: Surface Plot of tube diameter vs water mass flow rate vs exit quality

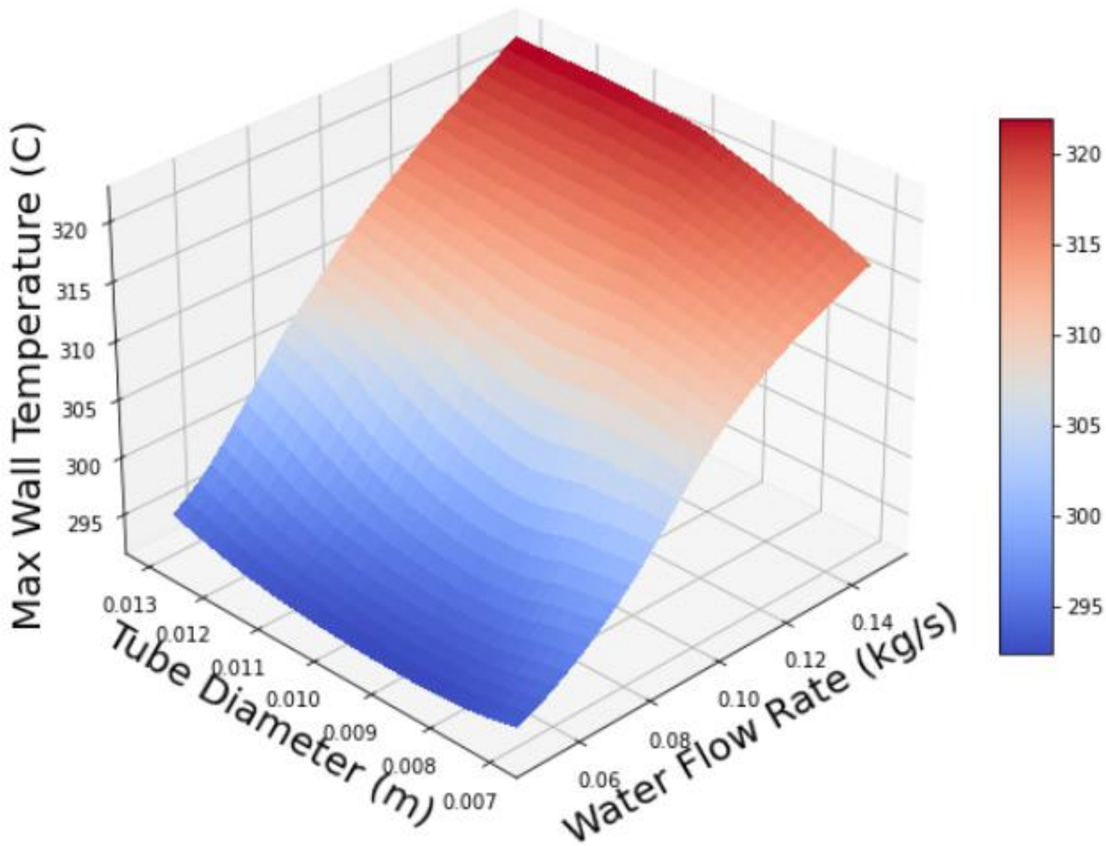


Figure 13: Surface Plot of tube diameter vs water mass flow rate vs maximum wall temperature

With this model, in order to achieve an output quality of about 0.75 and a maximum wall temperature that is no more than about 310ºC, the tube diameter should be 9mm with a water mass flow rate of 0.09 kg/s

H. The model was then compared to see if it better matches the data or shows signs of overfitting.

- With the help of the derived mean absolute errors of the training dataset and validation set for both models, comparing them with each other, it can be observed that for the second model the error is lower implying it is better. Hence, the predicted data matches closely with the actual data on the second model.
- Observing the error for the training set and validation set, there is overfitting of both the models as the error is low for the train set but high for the validation set, showing the model predictions are inaccurate. But there is a clear improvement in the accuracy with the second model as the mean absolute errors obtained are very close to

each other proving that the dropout layers help reduce the chance of overfitting.

3. Task 1.3

This task aims at testing the understanding of creating an artificial neural network that contains four input parameters and one output parameter. This model should achieve a mean absolute error of 0.025 and be trained using a provided data set.

a. A data set that was provided that contains arrays for input data [D_i, q''_o, x_e, $T_{w,max}$] and an output parameter [$\dot{m}$] for the flow boiling depicted below.

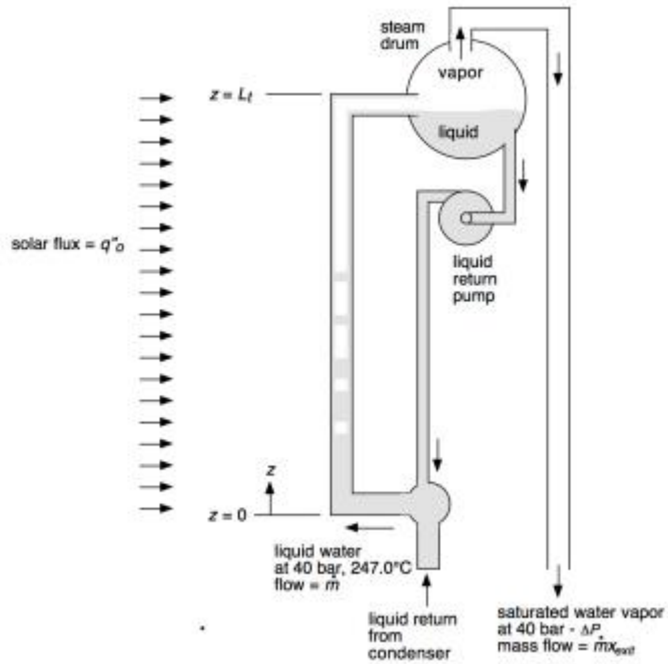


Figure 14: Flow Boiling

This data set was normalized by determining the median of each parameter and dividing each respective parameter by the median.

b. This normalized data is then separated into two data sets that are used for training and validation purposes with 3/4ths used for training the model.
c. This normalized and split data set is then input within a provided skeleton script.
d. To train this model, there were approximately ### epochs used and a learning rate that was decreased incrementally from 0.02 to 0.001. Ultimately, this model achieved a mean absolute error of 0.024741029 which falls below the required 0.025.

e. The trained model predictions are then compared to the trained data set values. In doing so, a mean absolute error of 0.03250644 is achieved for the predicted mass flow rate output vs the data value mass flow rate and can be better visualized in the log-log plot below.

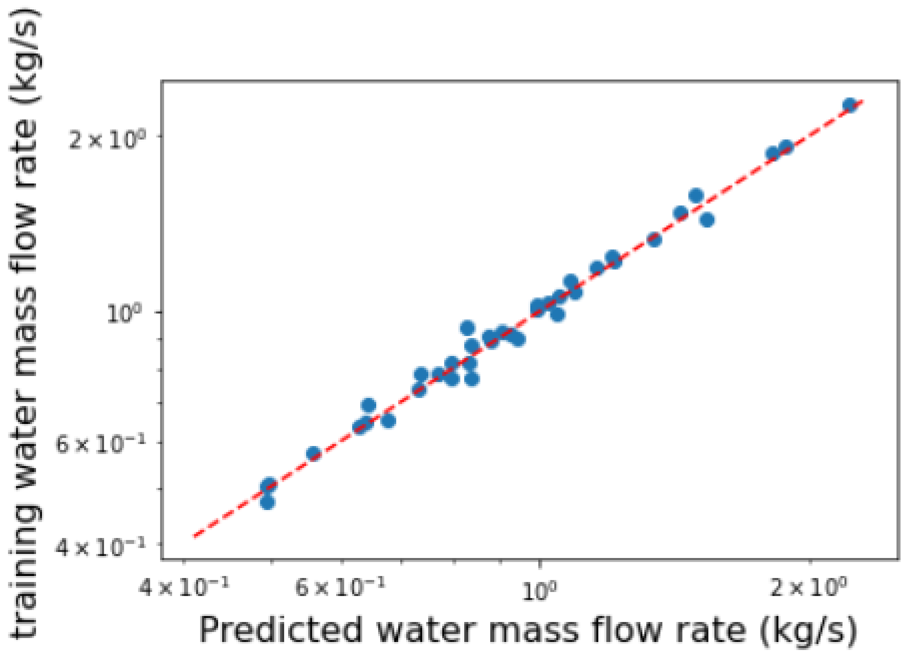


Figure 15: Log-Log plot of predicted vs training

f. This is then repeated for the validation data set which achieved a mean absolute error of 0.0513629 and the log-log plot below again visualizes that.

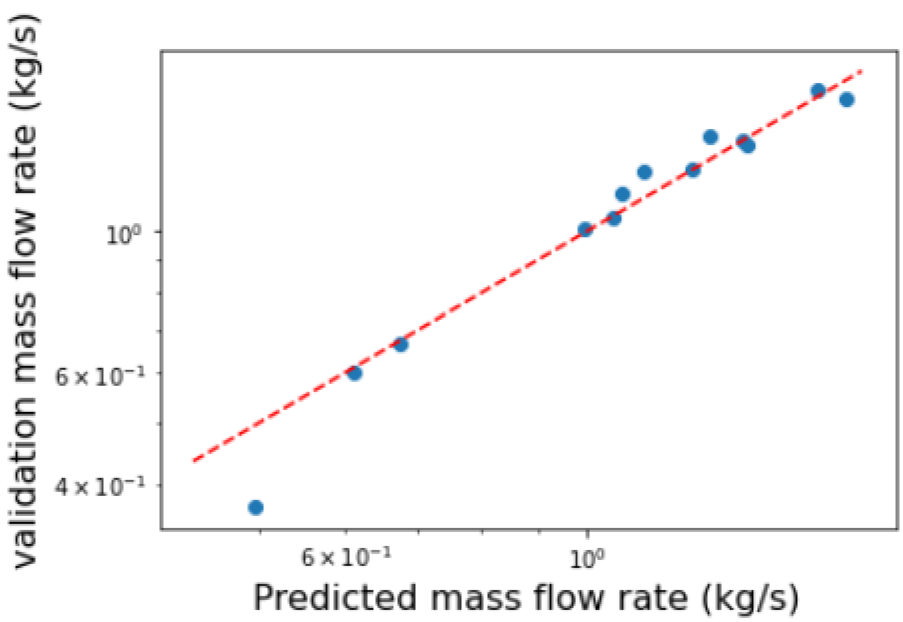


Figure 16: Log-Log plot of predicted vs validation

g. Lastly, a plot of water mass flow rate vs incident solar flux is created for a specific set of operating conditions. In this case, the inner tube diameter, the maximum wall temperature, and the exit quality is fixed, but the incident solar flux ranges from 500 to 800 kW/m^2. The plot can be found below.

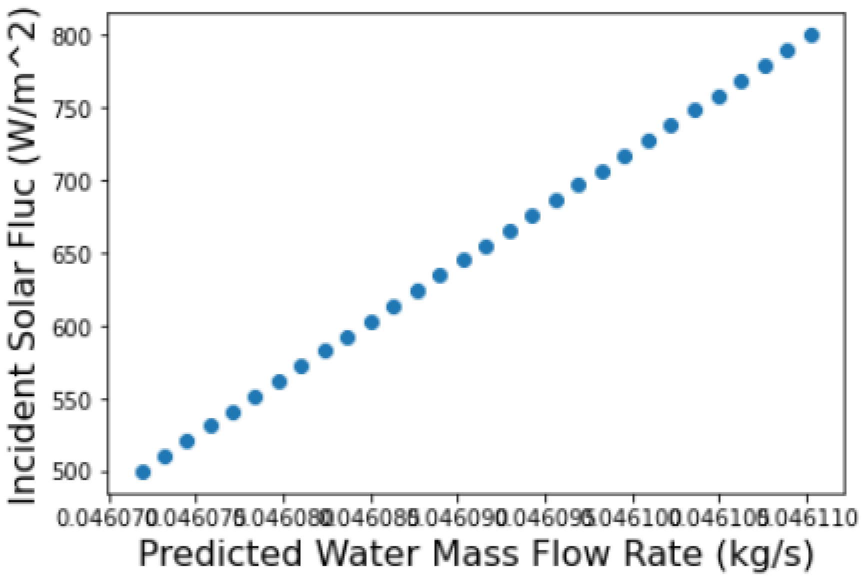


Figure 17: Log-Log plot of predicted vs training

IV. Part Two

In this part of the project a vertical surface with two electronic components is considered. It is known that when a heated vertical wall surface is put in still air it depicts a natural convection boundary layer flow as shown in fig 10. With this understanding, the same is assumed with the setup shown in fig 11, and the steady flow, heat transfer, and temperature field for the vertical wall are evaluated. For doing so an algorithm, explicit Forward-Time-Central Space (FTCS) is implemented. This algorithm helps to advance the temperature and velocity fields in time.

A computer program is prepared to perform the algorithm and the data values were determined for a spectrum of values of the three parameters [q_1", q_2", Δx_s] in the ranges 50 < q_1" < 600 W/m2, 50 < q_2" < 600 W/m2, and 0 < Δx_s < 0.010 m. Using these data values the objective of this part is to model and train a neural network model to predict the maximum surface temperature for a set of input values given which in turn helps to understand the performance of the system.

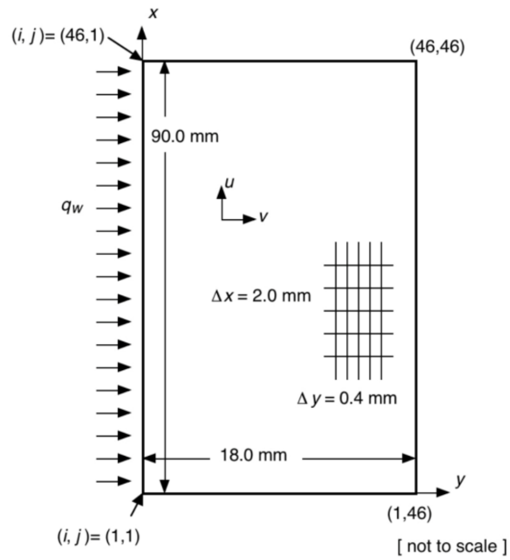


Figure 18: Natural convection boundary layer flow of a vertical heated surface setup used to perform the analysis

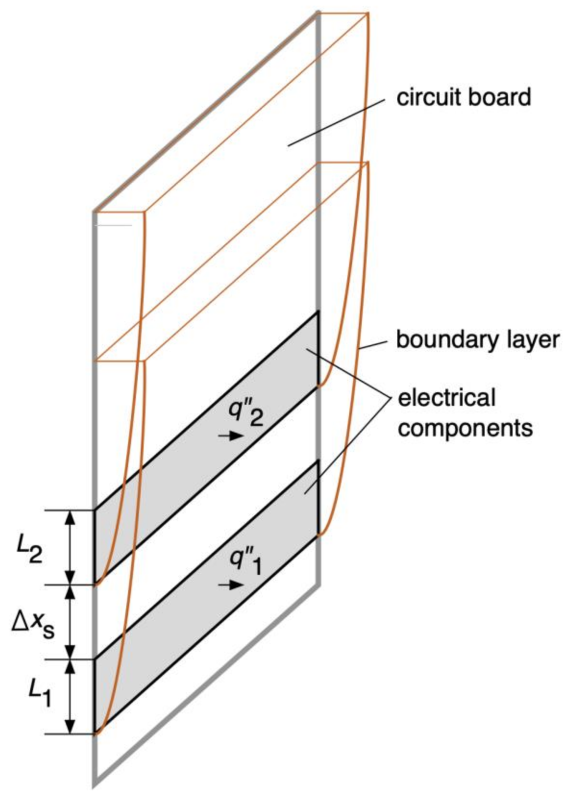


Figure 19: Setup for part two

1. **Task 2.1**

   This task develops a neural network model that predicts the maximum surface temperature for a set of input operating conditions.

a) Firstly the skeleton code was used to normalize the input data provided. The input data set contains arrays of the input data [q_1”, q_2”, Δx_s] and the output data parameters [$T_{s,max}$] for the natural convection-cooled, two-component circuit board system. These data sets are normalized by determining and dividing the median value of each parameter.

b) The new set of data was then randomly split between a training set and a validation set with ¾ of the data set being used for training. This is done using the scikit-learn, train_test_split function.

c) The normalized training data set is input within a skeleton script of a neural network. A sequential neural network named “model2max” is created. Based on the experience and class lectures, the number of inputs, the number of hidden layers, and the number of neurons within each layer are selected. The challenge is to make it complex enough to accurately fit the data, but not make it too complex where the model is overfitted to the data or requires too many iterations to reach convergence. Using this basic architecture the model2max network model is created with an input layer of 8 neurons(two times the number of input parameters), and an input_shape of 4. There are four hidden layers created with 12, 24, 16, and 8 neurons respectively. All the layers are assigned the relu activation function. Finally, an output layer with 1 neuron is created.

d) By training the model with the training set and adjusting the learning rate, the model reached a mean absolute error loss of 0.024551701439278466 ^oC, which was well below the 0.025 goal. To achieve this the model was run five times, where with each iteration the learning rate was reduced with increasing the number of epochs. As the tries increased the patience was parallelly increased to incorporate more epochs to be considered. The final learning rate used is 0.00035 and the model was trained for 4892 epochs in total.

e) With the trained model, the predicted values were compared to the data set and can be visualized below in the logarithmic plot. With the predicted and trained value data, the mean absolute error was calculated to be 2.753797470842088 ^oC which proves that the model trained is accurate.

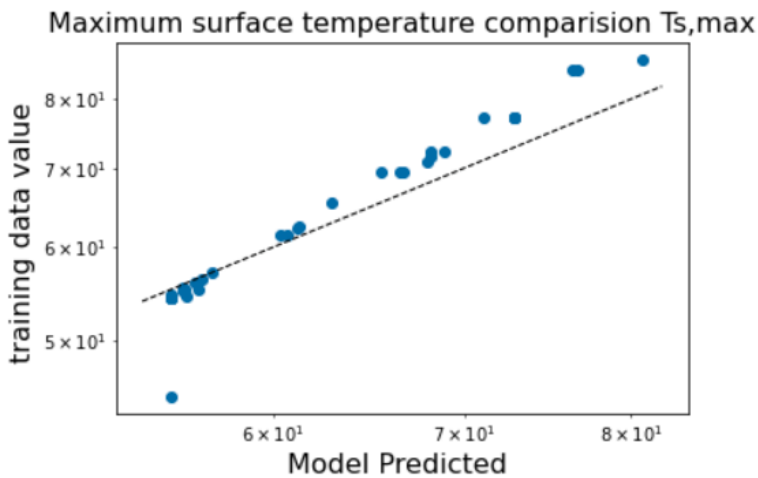


Figure 20: Log-Log plot of predicted vs training

f) The trained model was then verified for accuracy and potential overfitting through the use of the validation data that comprised ¼ of the originally provided data set. In doing so, a separate log-log plot was created to compare the predicted values which can be seen below in the logarithmic plot. The mean absolute error was also calculated to be 1.6971183647712074 ^{o}C which shows the data is overfit.

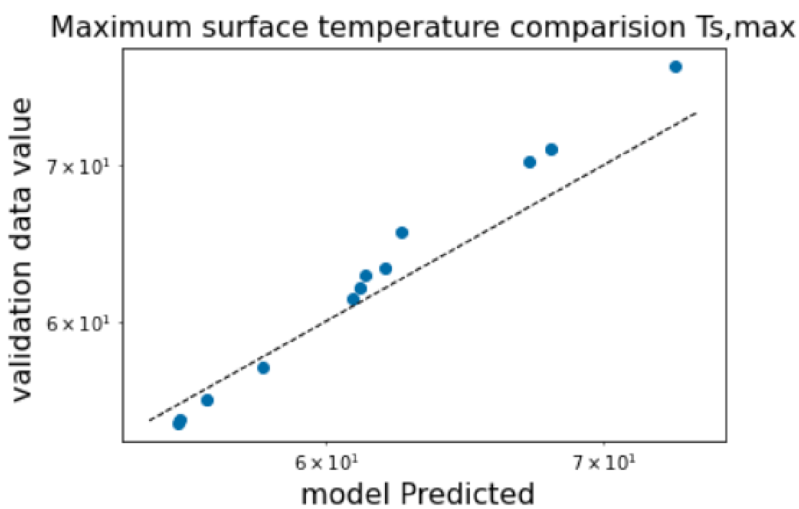


Figure 21: Log-Log plot of predicted vs validation

g) In obtaining a trained neural network, the neural network was used to determine the variation of Ts,max for a set of operating conditions. Taking the heat flux of both components to be the same[q_1"= q_2''=$q_{1\&2}$''], 100 < $q_{1\&2}$''< 500W/m^2 and 0.0 < Δx_s < 0.015m a surface plot is created for Ts,max as a function of $q_{1\&2}$'' and Δx_s.

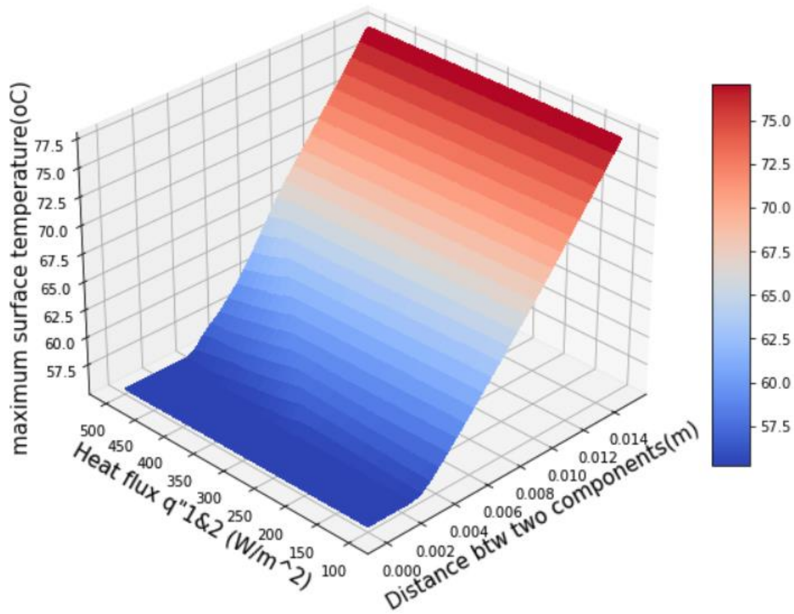


Figure 22: Surface plot of maximum surface temperature against heat flux and distance between the two components.

With the help of the surface plot for having a maximum wall temperature of not more than 72^{o}C, the components are clearly to be placed with a vertical spacing of not more than 9 mm for varying heat flux.

V. Work Distribution

Throughout the project timeline, the work was individually done and then compared as most tasks were to be done by every member. Using GitHub, and living close in proximity, the team was able to easily collaborate. The report was worked on collaboratively.

VI. Appendices

1. Figures

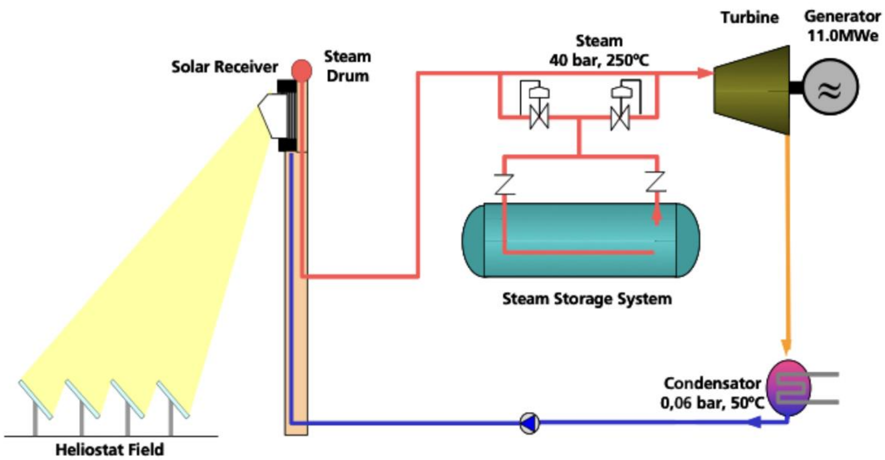


Figure 1: Representation of boiler mechanism used to generate steam to in turn generate electricity.

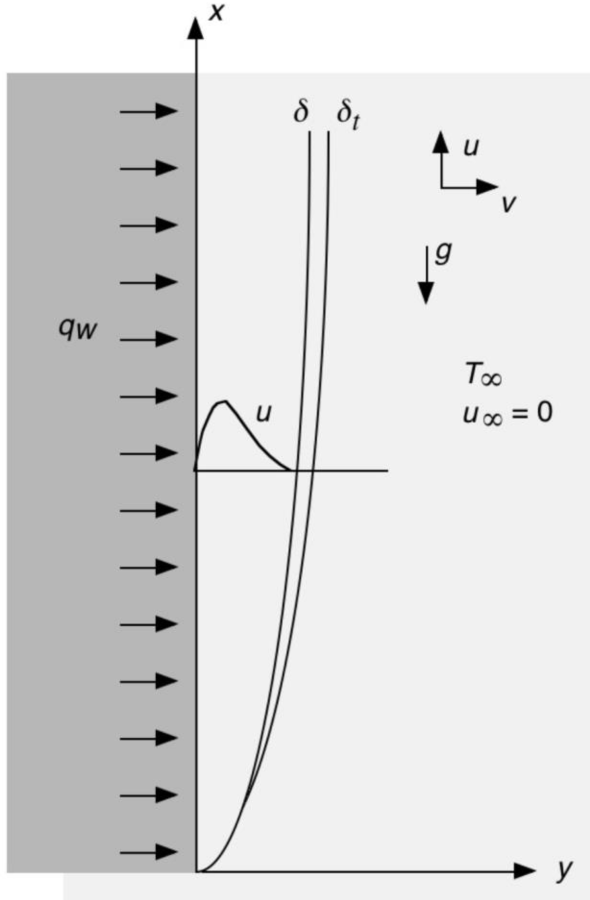


Figure 2: Representation of natural convection boundary layer flow of a heated surface in still air.

Figure 3: PS10 Solar Thermal Power Plant

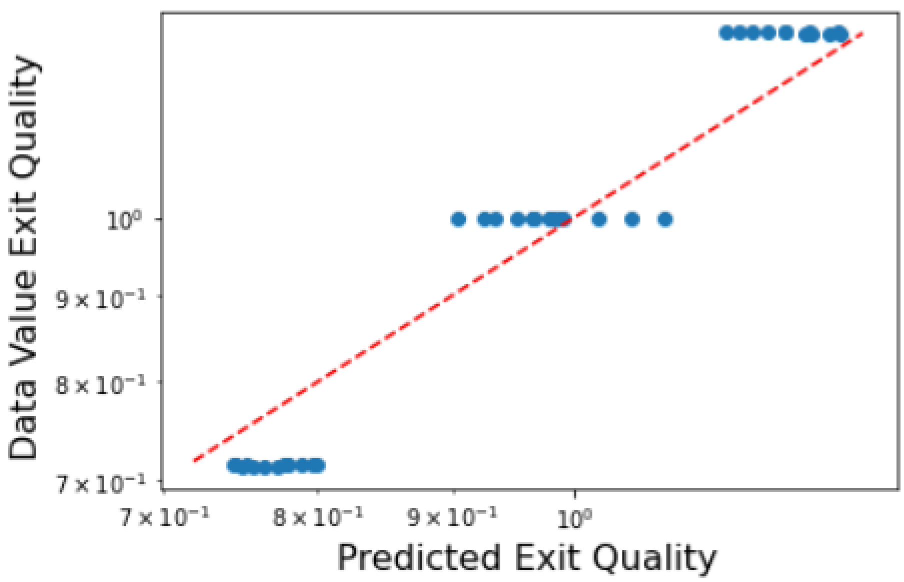


Figure 4: Log-Log plot of predicted vs training

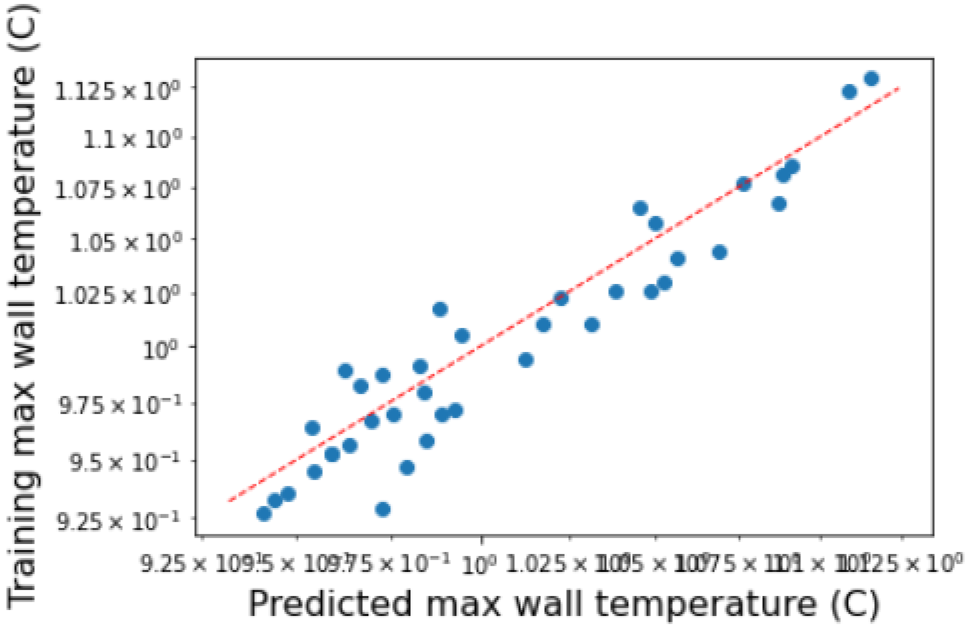


Figure 5: Log-Log plot of predicted vs training

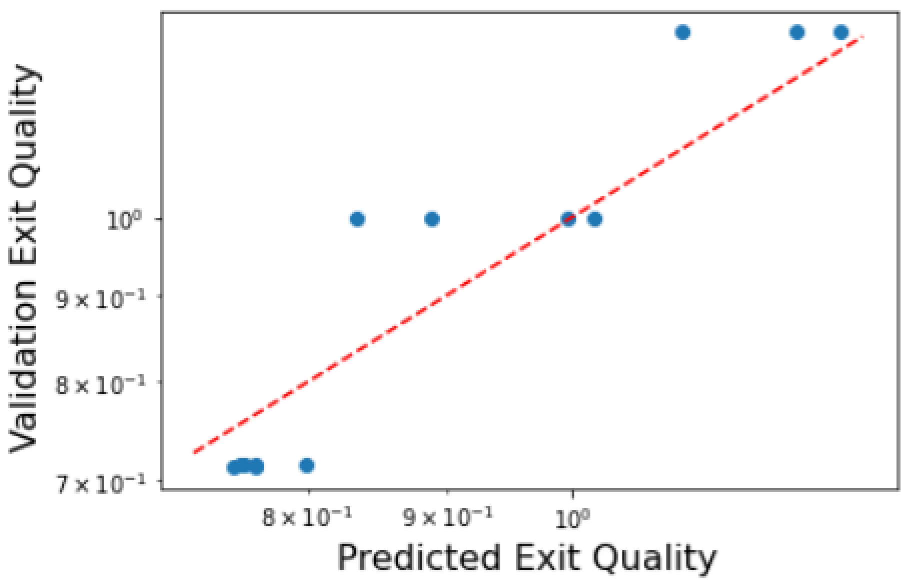


Figure 6: Log-Log plot of predicted vs training

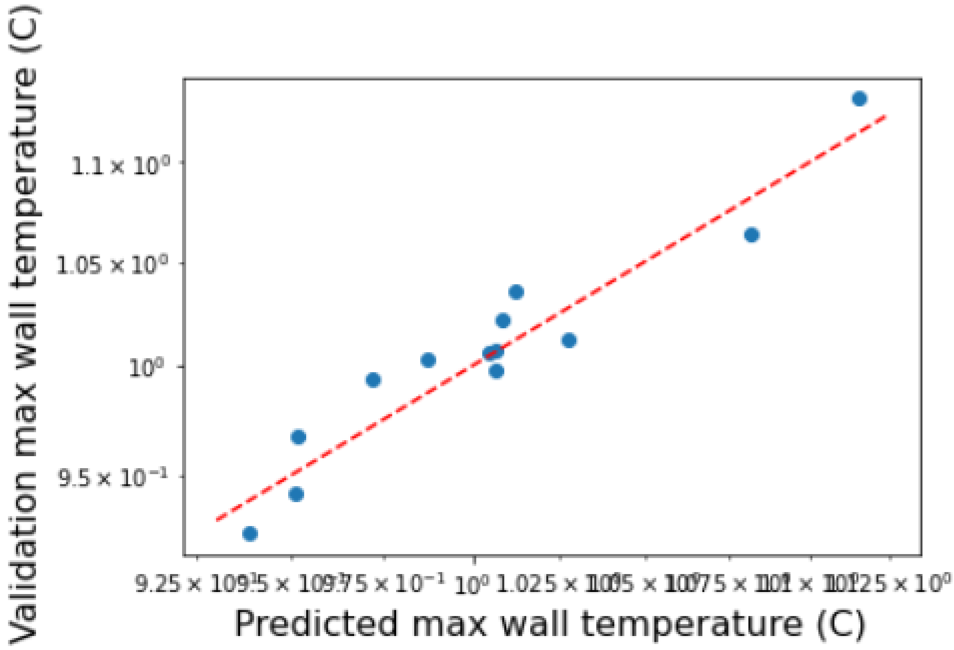


Figure 7:Log-Log plot of predicted vs validation

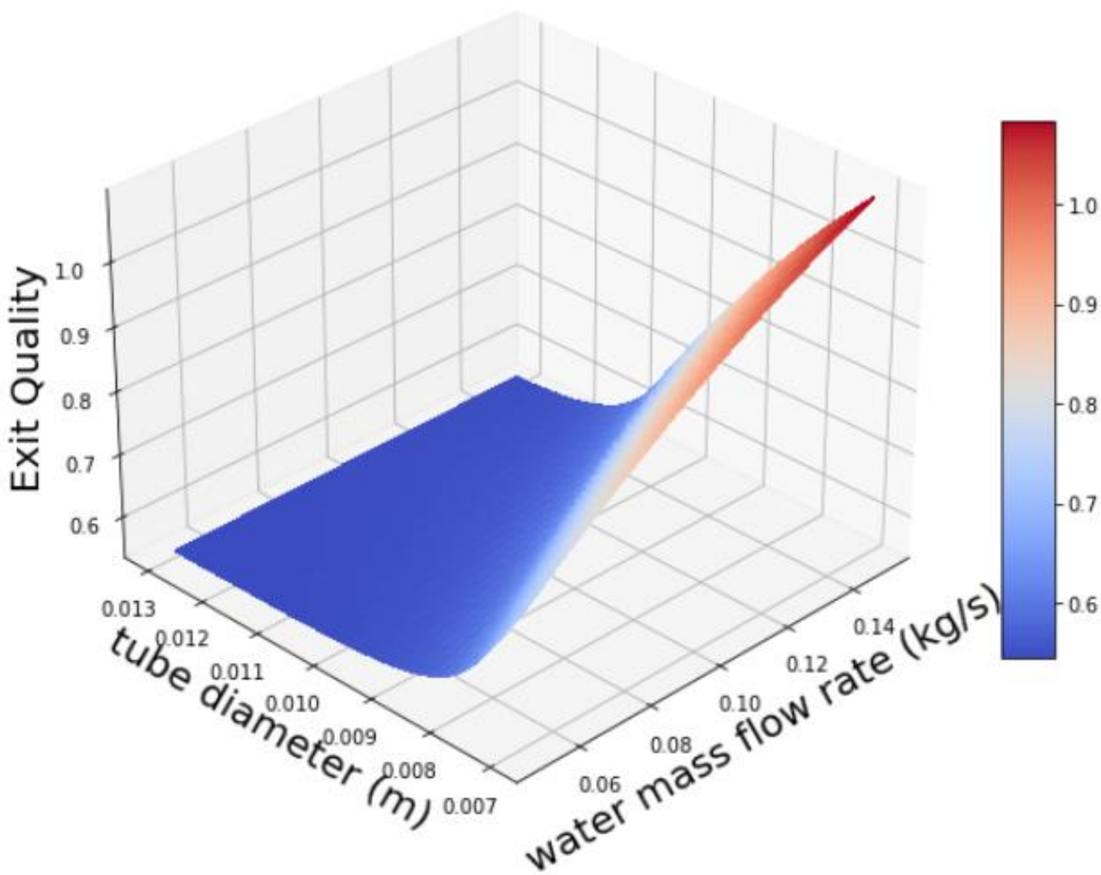


Figure 8: Surface Plot of tube diameter vs water mass flow rate vs exit quality

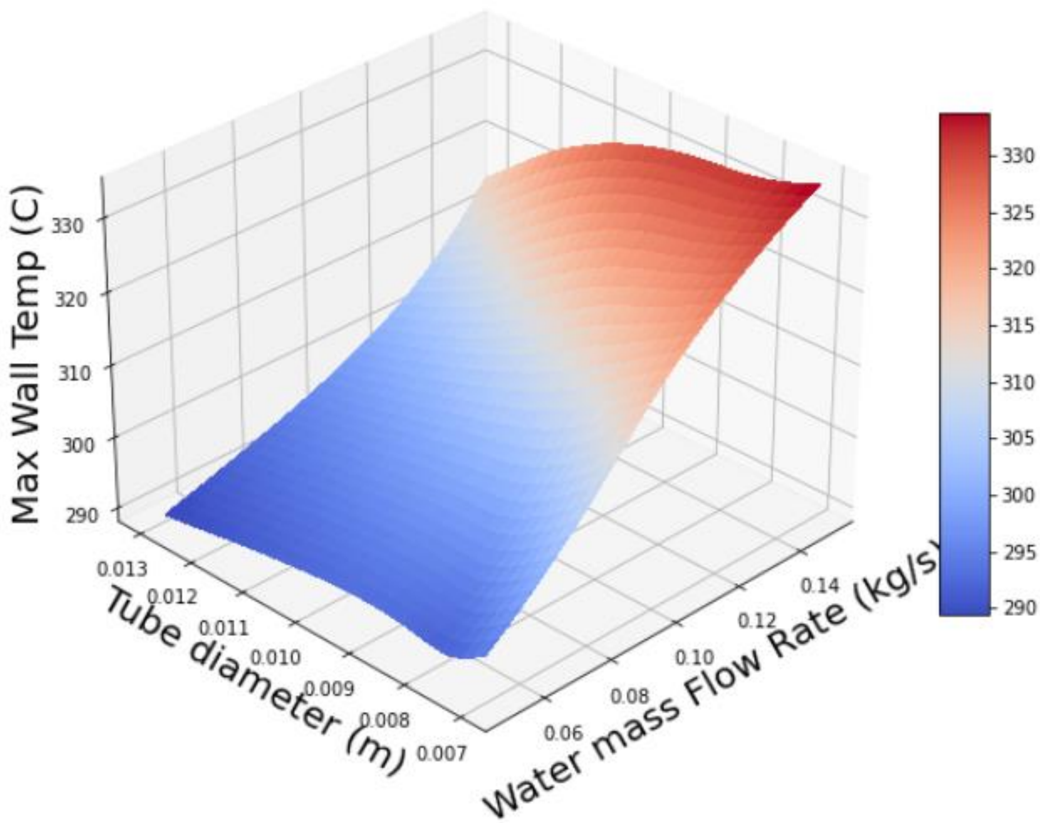


Figure 9: Surface Plot of tube diameter vs water mass flow rate vs maximum walltemperature

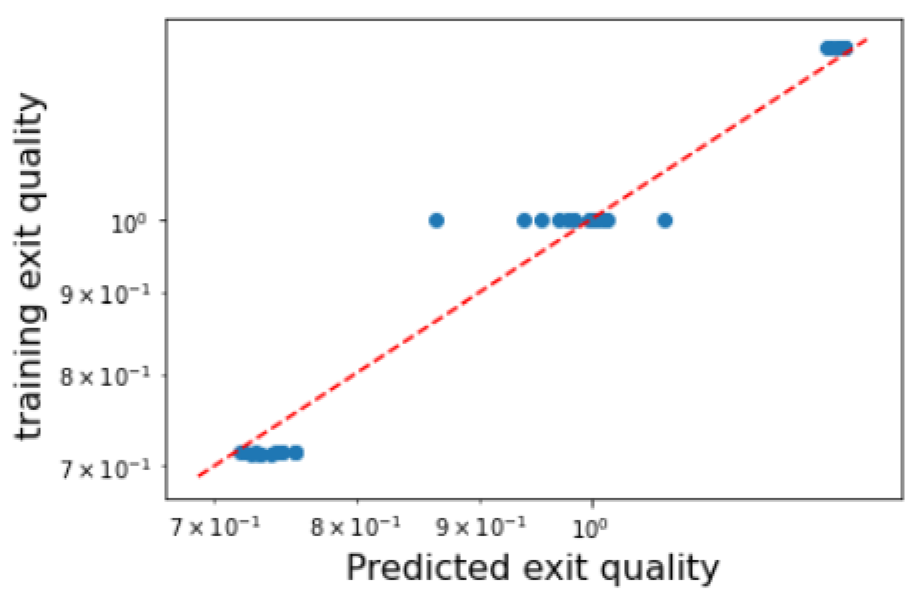
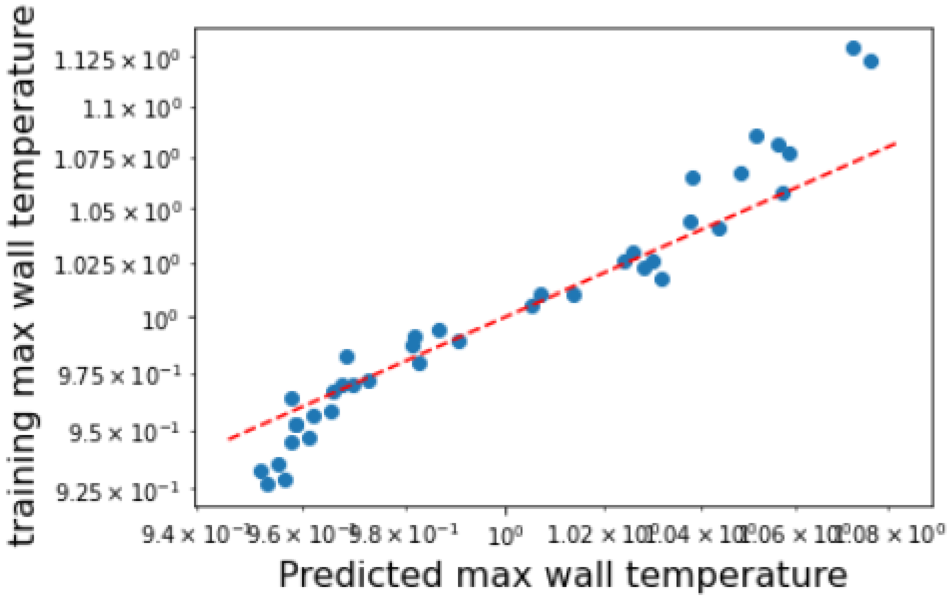


Figure 10: Log-Log plot of predicted vs training



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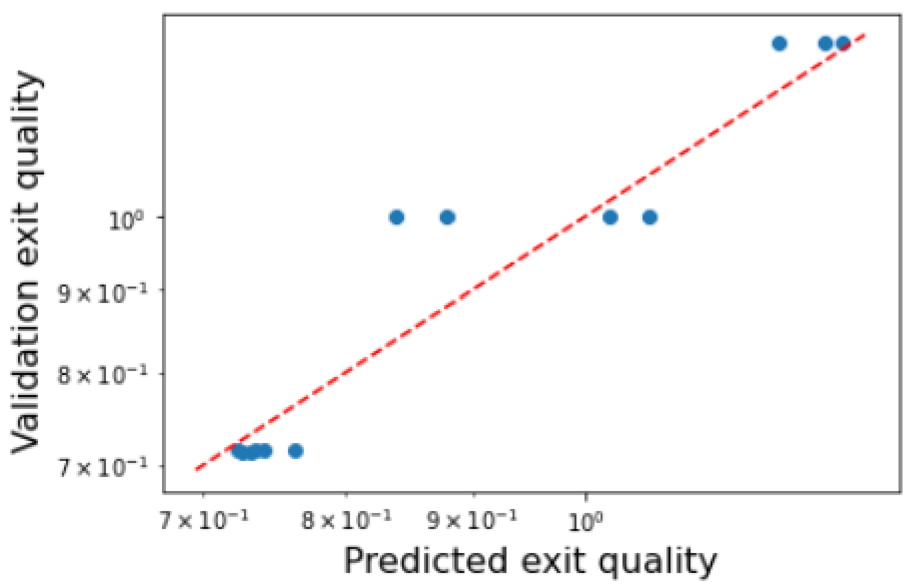

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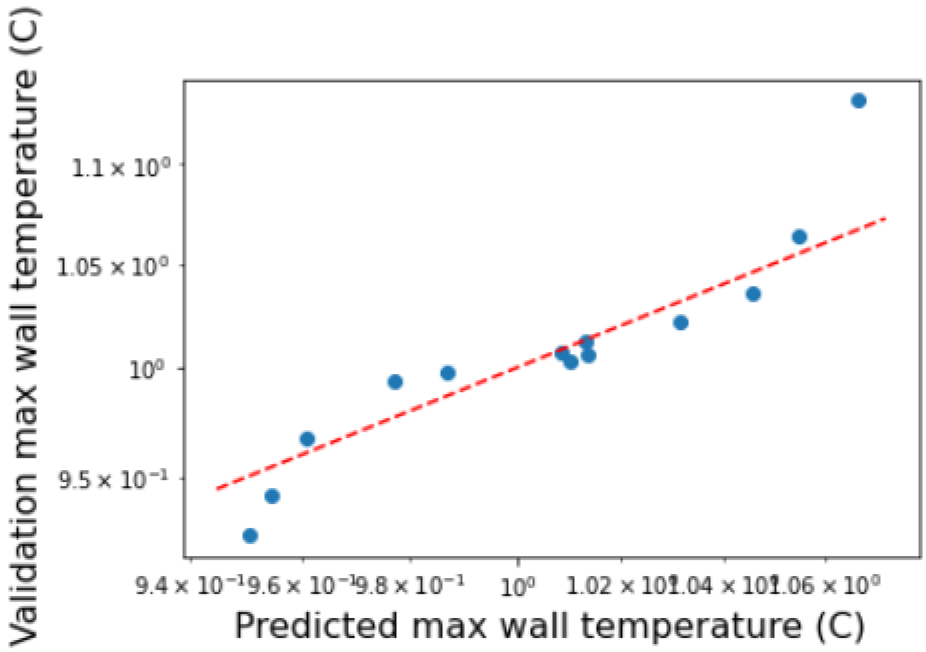

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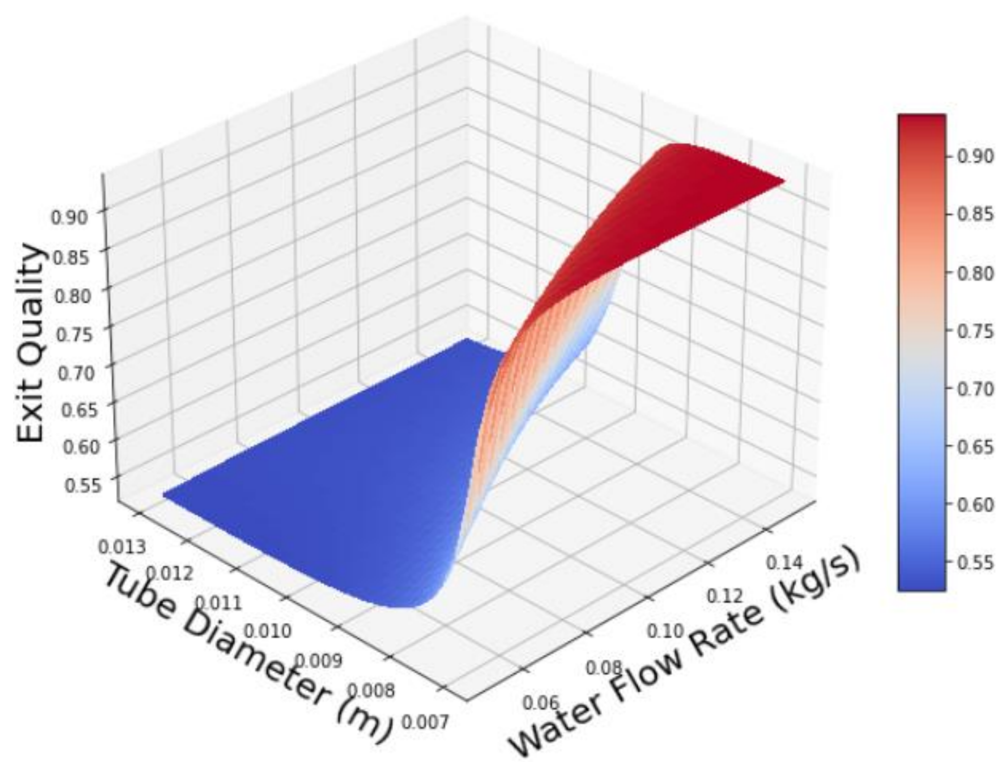

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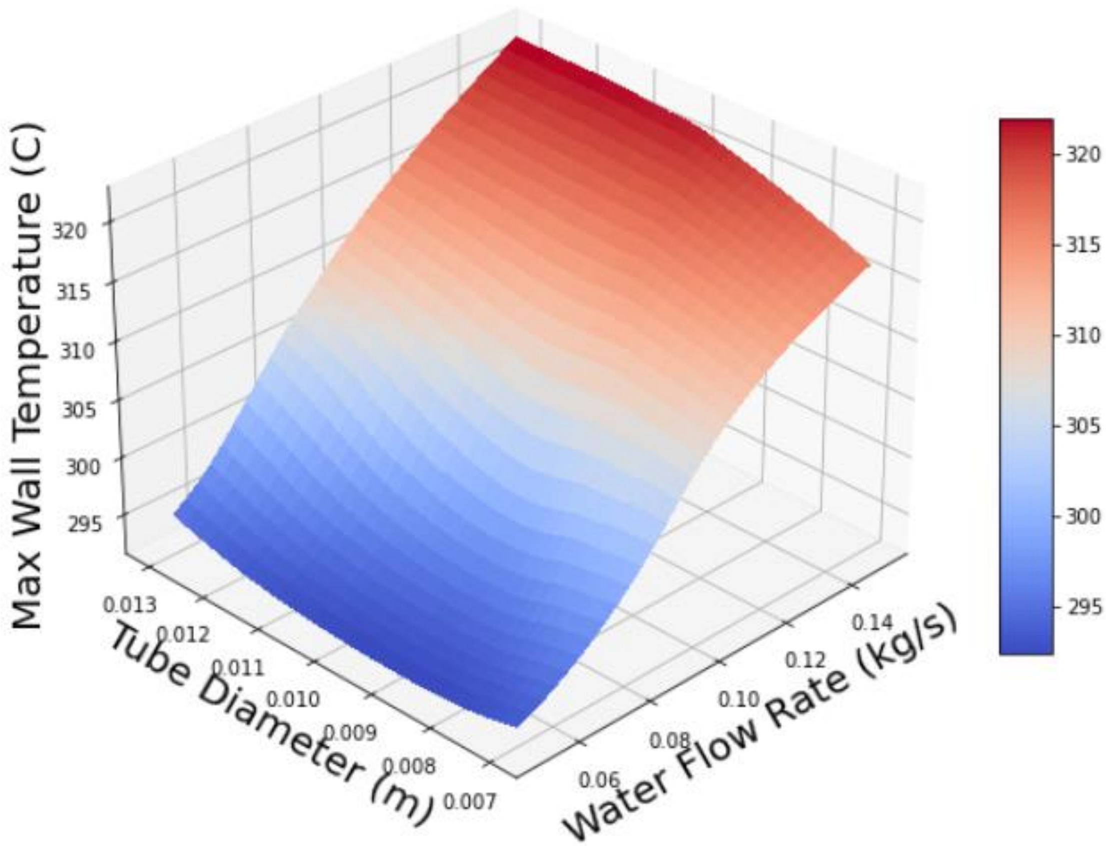

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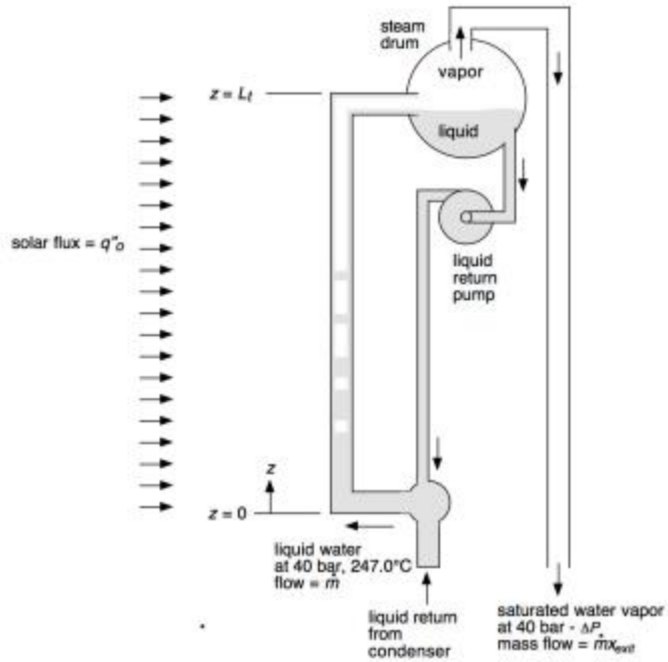
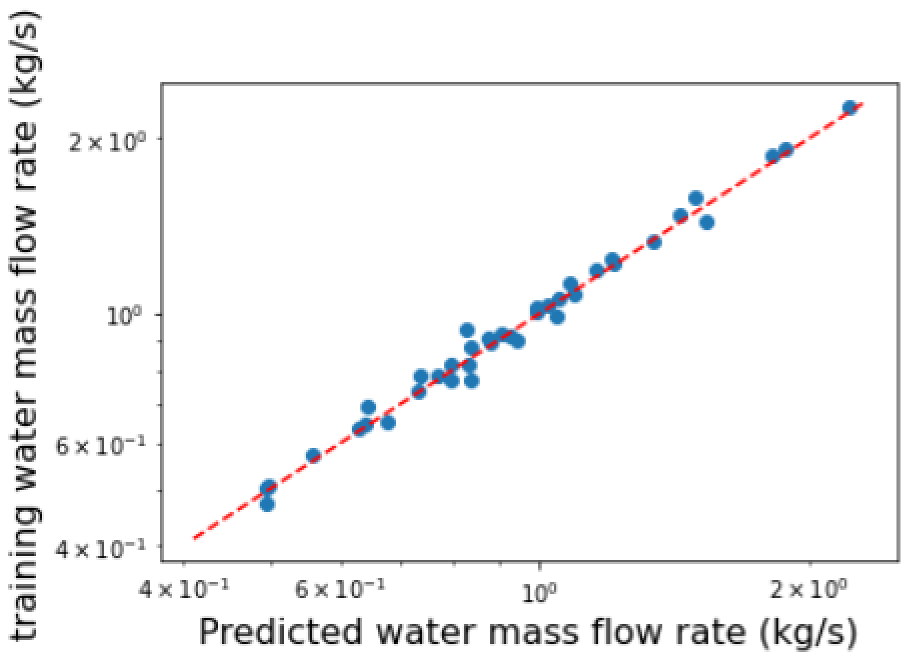


Figure 16: Flow Boiling



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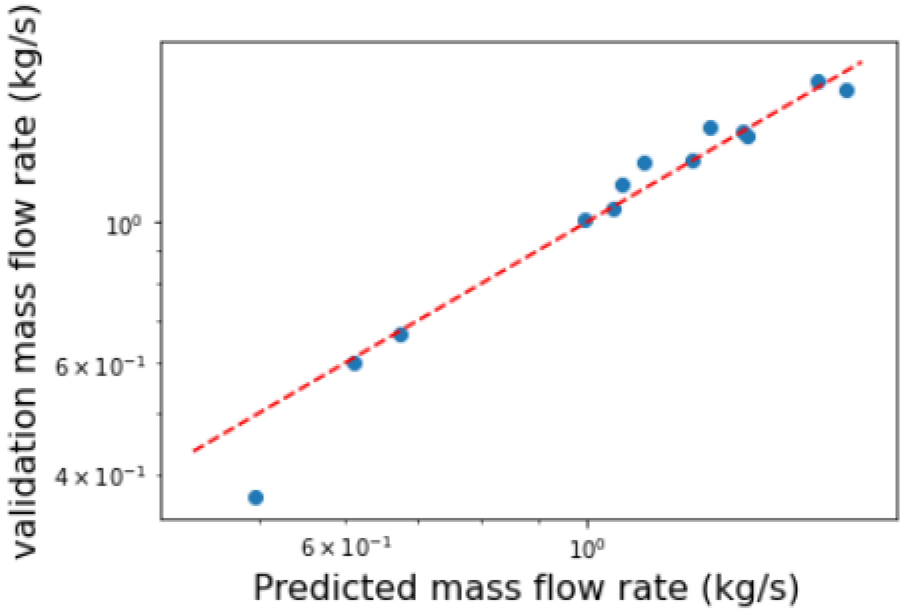

Figure 18: Log-Log plot of predicted vs validation

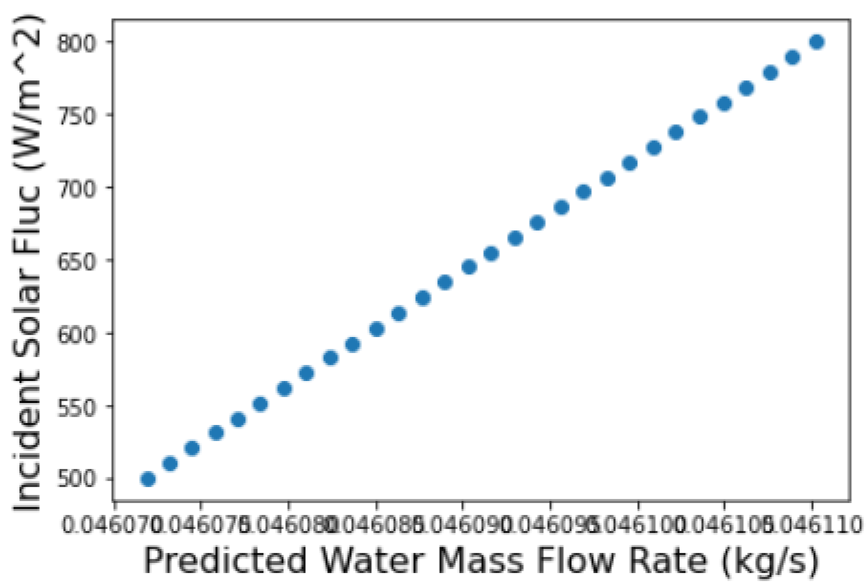

Figure 19: Log-Log plot of predicted vs training

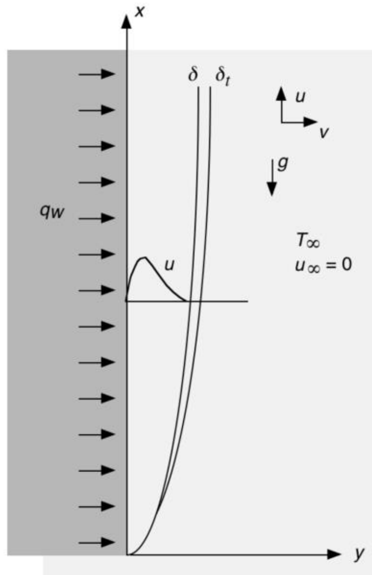

Figure 20: Natural convection boundary layer flow of a vertical heated surface in still air

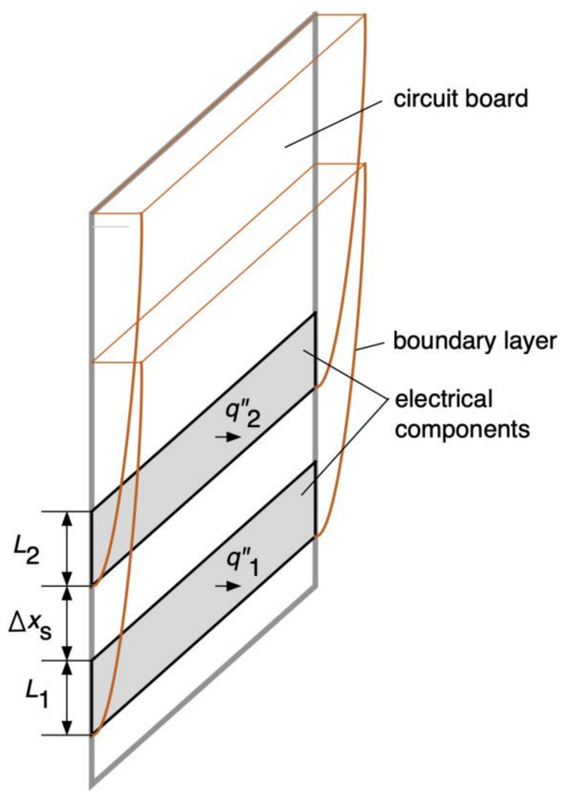

Figure 21: Setup for part two

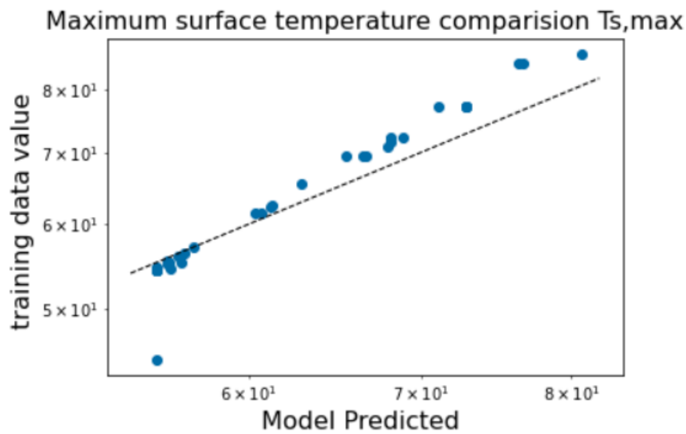

Figure 22: Log-Log plot of predicted vs training

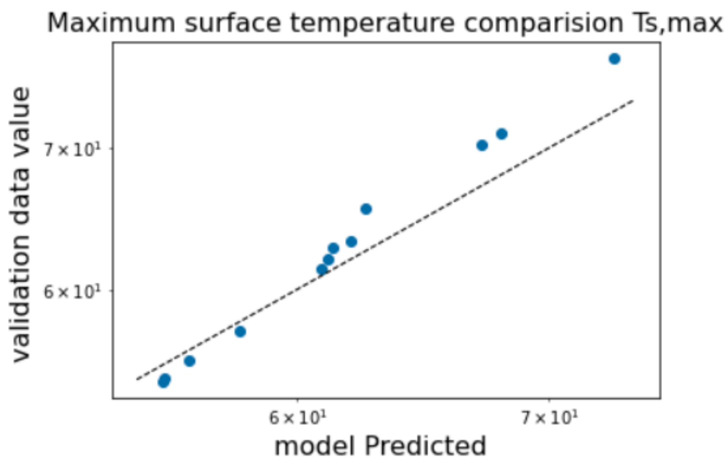

Figure 23: Log-Log plot of predicted vs validation

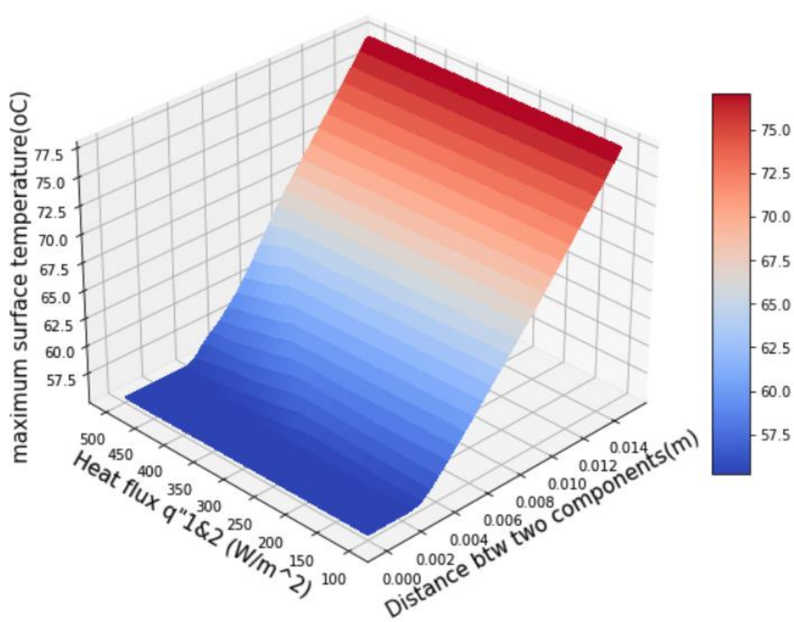

Figure 24: Surface plot of maximum surface temperature against heat flux and distance between the two components.

2. Code