Report
Project 4 - May 12th 2021

ME 249 – Machine Learning Tools for Modeling Energy Transport and Conversion Processes

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Task 1.1

a) We determine the median for each parameter and normalize the data points (**Figure 1**).

```
Median of each input: [1.100e-02 8.500e+02 9.265e-02]
xe median : 0.735
Normalized output array: [[0.71428571 1.00656383]
 [0.71428571 0.97965212]
 [0.71428571 0.96652445]
```

Figure 1 - *Normalization of data*

b) We use sklearn to define our training and validation set with respective sizes of ¾ &¼ % of the dataset (**Figure 2**).

```
from sklearn.model_selection import train_test_split

x_train, x_test, y_train, y_test = train_test_split(x_norm, y_norm, test_size=0.25)
```

```
Length of training set: 39
Length of testing set: 13
Length of the entire set: 52
```

Figure 2 - *Definition of training and validation sets*

c) & d) We use the given neural network with 3 hidden layers of 8, 16 & 8 neurons. The activation function is ELU. The optimizer is RMSprop. Now, we train the model with the previous defined training data. We obtain a minimum loss value of 0.011.

e) We plot the predictions with the training data and compare with our data points (**Figure 3**). We obtain a minimum absolute error (MAE) of 0.032 for the exit quality and 0.0039 for the maximum temperature of the wall.

```
MAE with exit quality data points: 0.031518047127905 84
MAE with Tw data points: 0.0038547955933222722
```

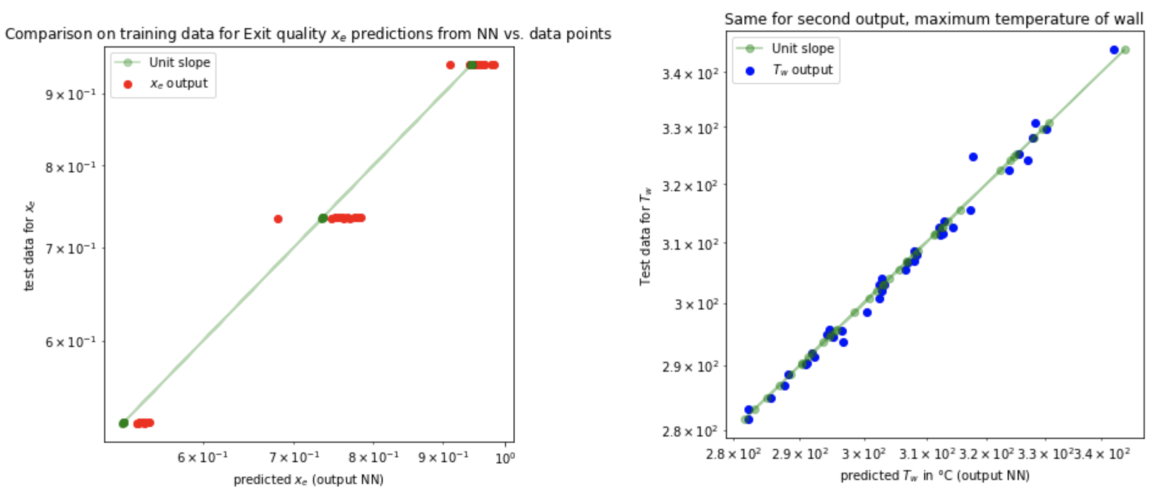

Figure 3 - *Predictions vs. training data points for both outputs*

We obtain predictions that are well correlated with the data points and with very small MAE for both outputs. We can conclude that the neural network is doing a nice job on the training data as expected.

f) We do exactly the same as in part e), however now we use the validation set. We obtain the following scatter plot (**Figure 4**). We obtain a MAE of 0.037 for the exit quality and 0.0055 for the maximum temperature wall.

```
MAE with exit quality validation data points: 0.03682330547983518
MAE with Tw validation data points: 0.005515458902176631
```

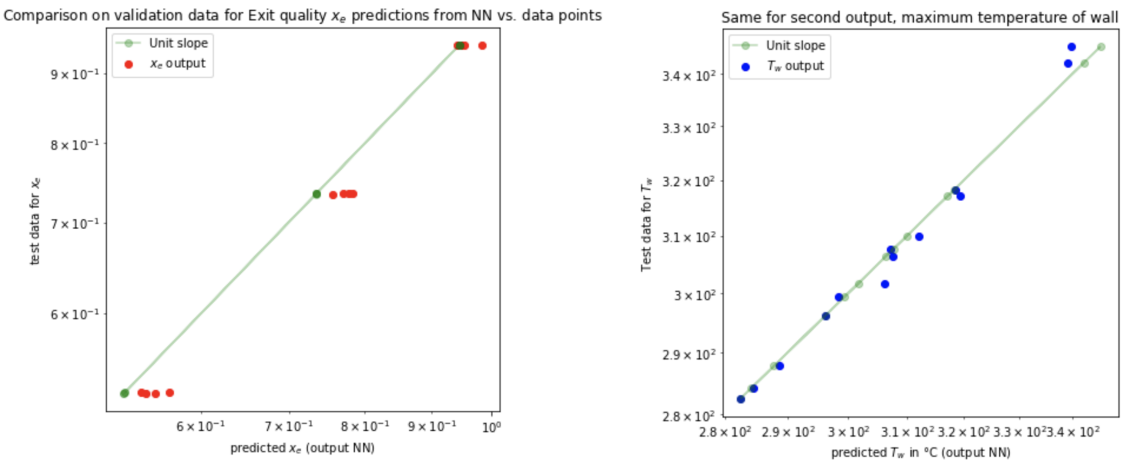

Figure 4 - *Predictions vs. validation data points for both outputs*

It seems that the model is doing well on the validation set. Both MAE for the outputs are slightly greater than previously with the training dataset. However, it is logical and the plots show that it is well predicted. We do not see signs of overfitting for the first model.

g) We create two surface plots for each output (**Figure 5**).

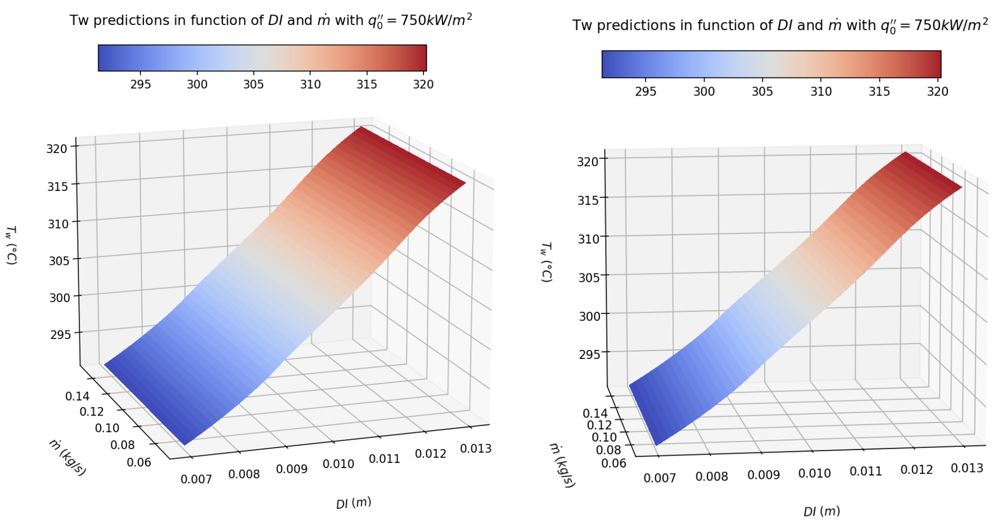

Figure 5 - *Surface plots for each output (x_e & T_w)*

From those plots, **we can approximate a value of DI = 10.5 mm and any value for $\dot{m}$** to obtain an exit quality of 0.75 & a maximum wall temperature less or equal to 310°C.

Task 1.2

We repeat the same procedure as in task 1.1. The only difference is that we have a more complex neural network with dropout layers after each hidden layer (Figure 6).

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_22 (Dense)             (None, 6)                 24
_________________________________________________________________
dense_23 (Dense)             (None, 8)                 56
_________________________________________________________________
dropout_5 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_24 (Dense)             (None, 12)                108
_________________________________________________________________
dropout_6 (Dropout)          (None, 12)                0
_________________________________________________________________
dense_25 (Dense)             (None, 16)                208
_________________________________________________________________
dropout_7 (Dropout)          (None, 16)                0
_________________________________________________________________
dense_26 (Dense)             (None, 8)                 136
_________________________________________________________________
dropout_8 (Dropout)          (None, 8)                 0
_________________________________________________________________
dense_27 (Dense)             (None, 2)                 18
=================================================================
Total params: 550
Trainable params: 550
Non-trainable params: 0
```

Figure 6 - *New neural network model*

We were only able to reach a minimum loss value of 0.045.

With the validation dataset, we obtain the following results (**Figure 7**).

```
MAE with exit quality training data points: 0.043075404498144976
MAE with Tw training data points: 0.0443548364790881
```

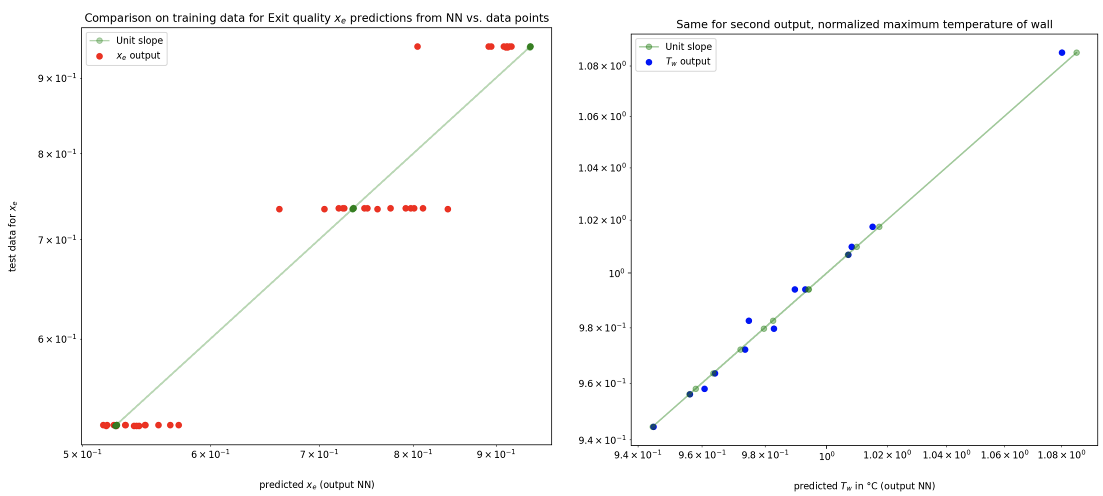

Figure 7 - *Predictions on the training dataset with the new neural network*

We obtain a MAE of 0.043 and 0.044 for the exit quality predictions and maximum wall temperature. The MAE is roughly the same as with the previous neural network.
Moreover, the plots show that the neural network makes relevant predictions close to the real data points.

With the validation dataset, we obtain the following results (**Figure 8**).

```
MAE with exit quality validation data points: 0.0641400447133821
MAE with Tw validation data points: 0.032928533282740674
```

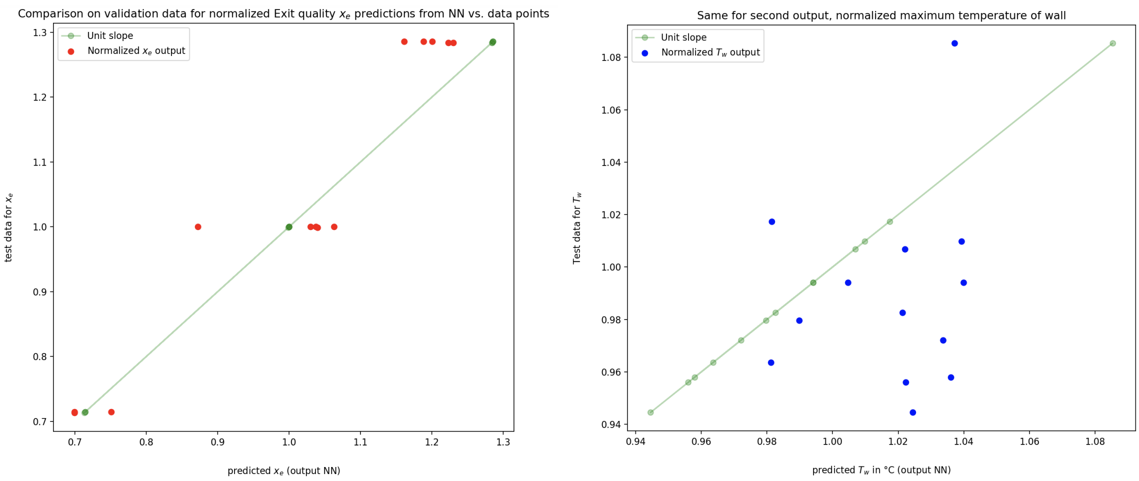

Figure 8 - *Normalized predictions on the validation dataset with the new neural network*

The MAE for the exit quality output is slightly bigger than on the training dataset with 0.064 instead of 0.043. Again, we do not see signs of overfitting with this new neural network. However, the predictions of the maximum wall temperature are not extremely close to the unit slope.

```
13/13 [==============================] - 0s 22ms/step
Test loss: 0.04727175459265709
Test accuracy: 0.7692307829856873
```

```
39/39 [==============================] - 0s 96us/step
Train loss: 0.043873498359551795
Train accuracy: 0.8461538553237915
```

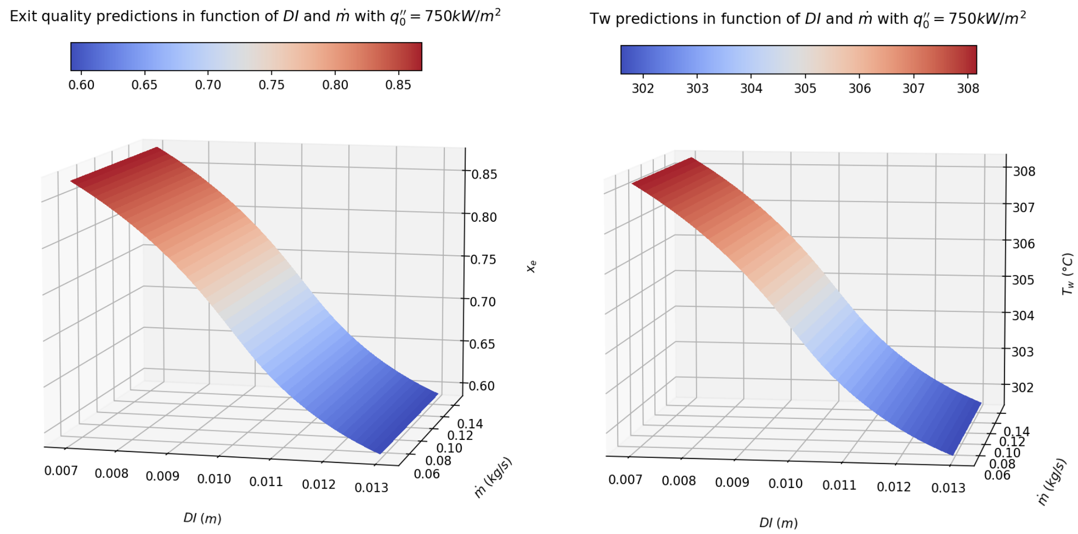

Figure 9 - *Surface plot for each output (x_e & T_w)*

The second neural network reaches similar performance as the first neural network. In both cases, neural networks do not overfit the data and make relevant predictions. However, we would prefer the first neural network because the model is simpler - less hidden layer and therefore less parameters to train.

Task 1.3

a) We determine the median of the new data set with 4 inputs and one output parameter. We then normalize the data by dividing by the corresponding median as in the previous tasks (**Figure 9**).

```
Median of each input: [1.100e-02 8.500e+02 7.350e-01 3.047e+02]
output median : 0.09265
Normalized input array:  [[0.72727273 0.64705882 0.71428571 1.00656383]
 [0.72727273 0.76470588 0.71428571 0.97965212]
 [0.72727273 0.88235294 0.71428571 0.96652445]
 [0.72727273 1.         0.71428571 0.95241221]
 [0.72727273 1.11764706 0.71292517 0.94158188]
```

Figure 9 - *Medians and extract of normalized input array*

b) We divide the data into a training and validation set with sizes of 75% and 25% of the initial data set (**Figure 10**).

```
Length of training set: 39 ; Length of testing set: 13
Length of the entire set: 52
```

Figure 10 - *Lengths of training, validation and complete sets*

c) **& d)** We start our new design of neural network with the same activation function (ELU, the best performer) and we try to keep the same design as the first one (task 1.1) because it was simple and did a great job. We therefore try without dropout layers first and we will make appropriate changes if needed after.

```
Epoch 00736: early stopping
best epoch =  606
smallest loss = 0.017734770448162004
```

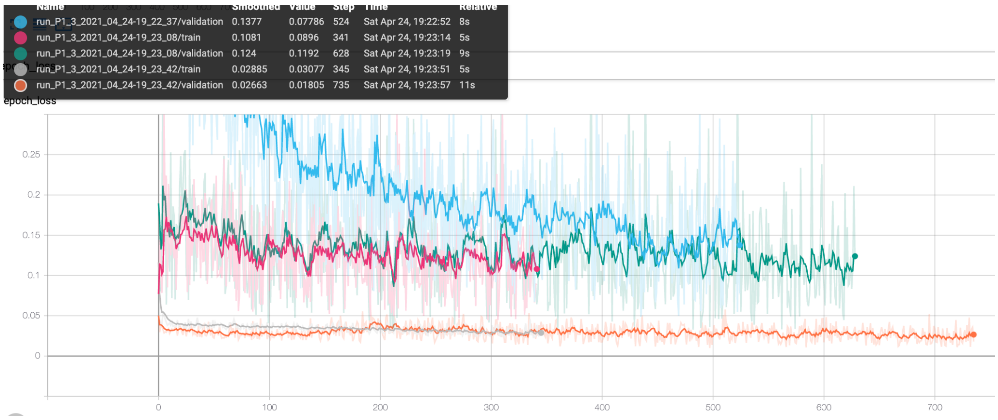

Figure 11 - *Smallest loss and tensorboard plots*

We easily obtain a smallest loss of 0.017 and the plots on tensorboard do not seem to show overfitting or other issues (**Figure 11**). At first sight, this neural network architecture is doing a good job.

e) We plot the predictions made by the model vs. the data points on the training data for the mass flow rate. We also calculate the MAE (**Figure 12**).

```
MAE with flow mass data points: 0.0333092517165046
```

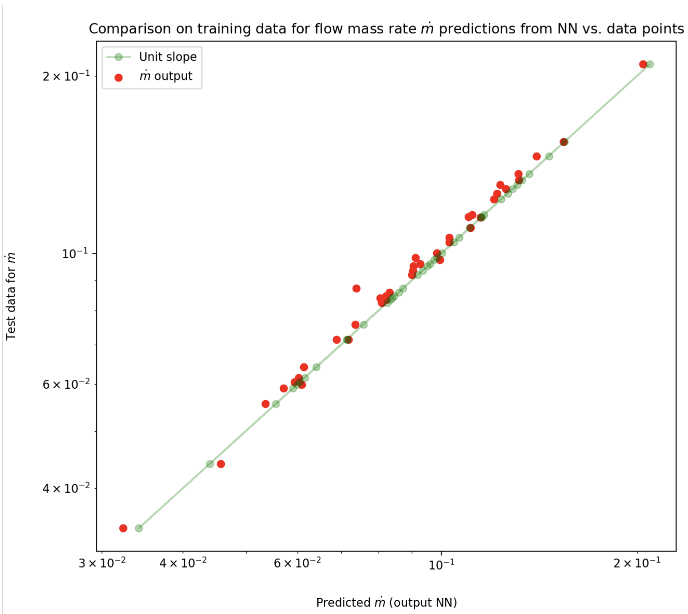

Figure 12 - *Prediction vs. data on the training set*

Most of the points are correctly predicted by the neural network as we can see on the plot. The MAE is 0.033 which is low as expected with our smallest loss. Globally, the neural network is doing a great job on the training data set.

f) We do exactly the same but with the validation data set.

```
MAE with exit flow mass rate validation data points: 0.01873649963510506
```

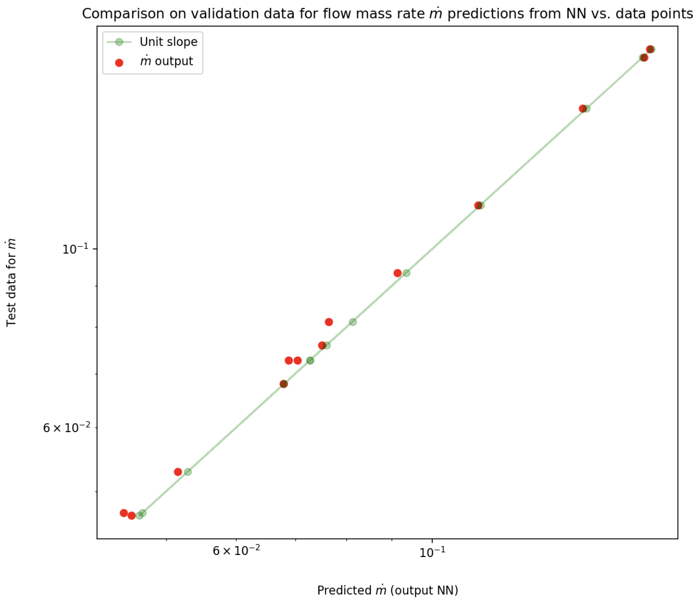

Figure 13 - *Prediction vs. data on the validation set*

The plot shows that data points are well predicted by the neural network and the MAE is slightly bigger than previously with 0.0187 but correct for validation data points. We do not see overfitting because the predictions have globally the same performance. Therefore, we do not change the neural network architecture with dropout layers.

Now, we use the model as part of a model-based control scheme.

We have $D_i = 0.010$ m, $x_e = 0.70$ and $T_{w,max} = 300$ °C. We plot the flow mass rate prediction for incident solar flux between 500 and 800 kW/m^2 (**Figure 14**).

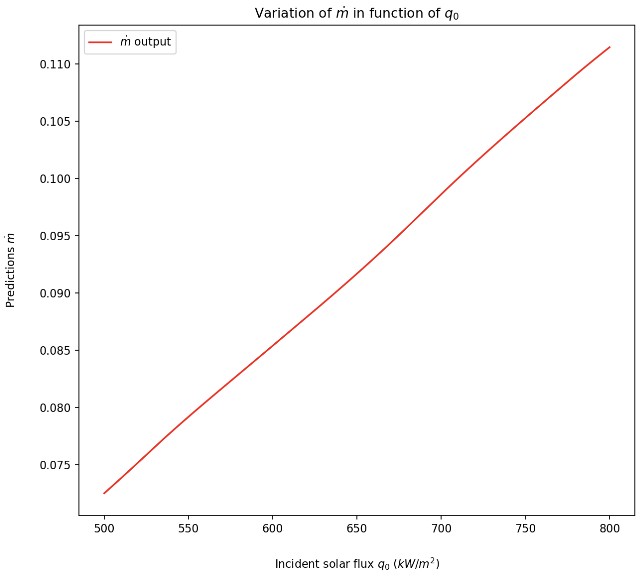

Figure 14 - *Variation of the flow mass rate in function of the incident solar flux*

We see that the flow mass rate follows a linear variation when the incident solar flux is the only variable parameter.

Part 2

Task 2.1

a) & b) We normalize the data by dividing by the median of each input/output. After, we separate the entire set into one training and testing set (**Figure 15**).

```
Median of each input: [2.e+02 2.e+02 4.e-03]
output median : 62.2

Length of training set: 35 ; Length of testing set: 12
Length of the entire set: 47
```

Figure 15 - *Medians and length of data sets*

c) & d) We use the previous training set to train our neural network. For the architecture, we start with ELU activation functions and we reuse the previous neural network design with 369 trainable parameters to see if it is also possible to reach a correct error.

We quickly reach a smallest error of 0.004 (**Figure 16**) and we therefore keep this architecture.

```
best epoch =  730
smallest loss = 0.004985054908320308

Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_15 (Dense)             (None, 6)                 24
_________________________________________________________________
dense_16 (Dense)             (None, 8)                 56
_________________________________________________________________
dense_17 (Dense)             (None, 16)                144
_________________________________________________________________
dense_18 (Dense)             (None, 8)                 136
_________________________________________________________________
dense_19 (Dense)             (None, 1)                 9
=================================================================
Total params: 369
Trainable params: 369
Non-trainable params: 0
```

Figure 16 - *Smallest loss error & Model summary*

e) We look at the predictions made by the model on the output $T_{S,max}$ and we compare it with the data points (**Figure 17**). We also compute the MAE.

```
MAE with Ts,max points: 0.012193715134289037
```

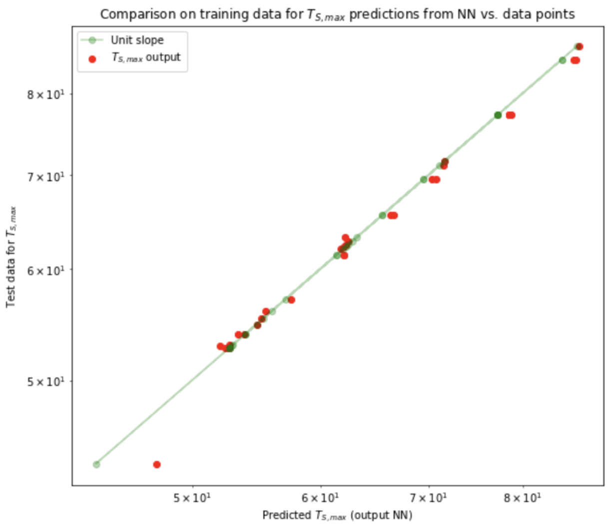

Figure 17 - *Plot of predictions vs. training data points*

We see the model is doing a great job and the predictions are correctly correlated. The MAE is also small and logical in comparison to the smallest error.

f) We do the same as previously but with the validation points (**Figure 18**).

```
MAE with Ts,max points: 0.012313193159471353
```

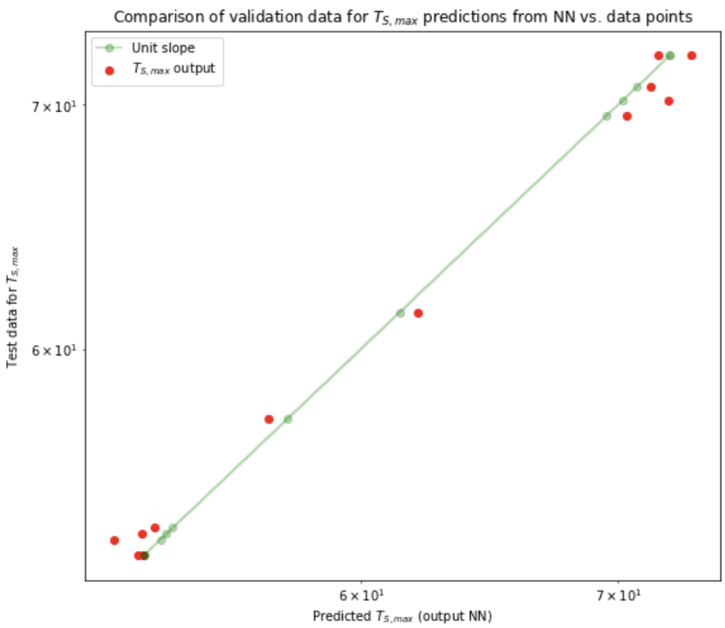

Figure 18 - *Plot of predictions vs. testing data points*

Again, the model is correct and we can see a great correlation between the predictions and the testing points. The MAE is also low, we do not see any proof of overfitting or underfitting.

h) We create a surface plot (**Figure 19**) for the following range of input values: $100 < q"_{2\&3} < 300\, W/m^2$ & $0.0 < \Delta x_s < 0.015\, m$

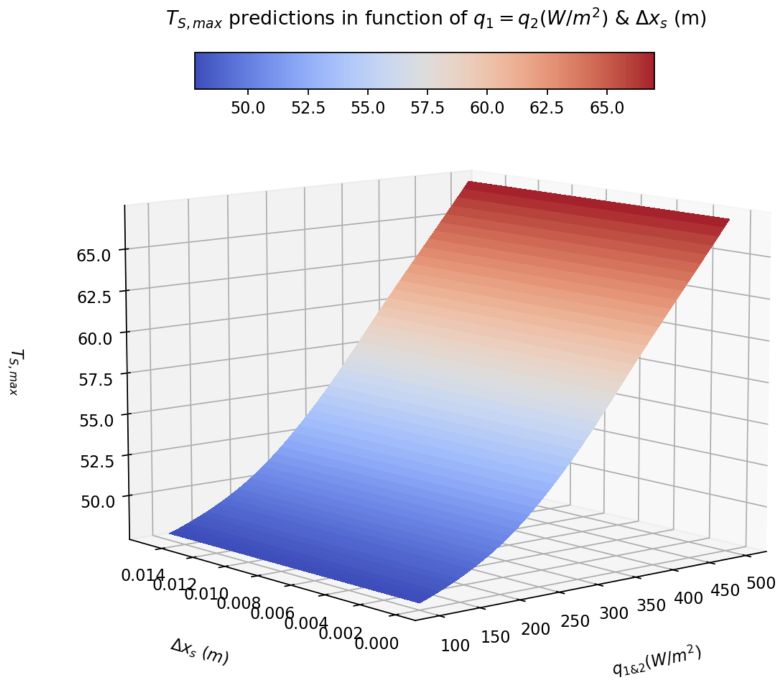

Figure 19 - *Surface plot for the predict output given the input values*

According to the previous plot (figure 19), any heat flux and component spacing allow a maximum component temperature $T_{s,max}$ below 75°C.

Division of the tasks:

We both worked on each part and compared our results.
The report has also been split evenly.