

To: President Frank O. Simpson, President, First-Order Systems, Inc.  
From: Neel Lingam, Andrew Gan, Nicholas Sherman, John Papas Dennerline  
RE: Final Technical Brief for the SCGL project  
Date: April 18, 2019

FOS requested an autonomous algorithm to analyze time history data from 5 different thermocouples and define 4 parameters, which will then be used to calculate statistics and prices. The criteria of the algorithm were comparing our test values to the given parameters and minimizing the SSE values, which determined the algorithm accuracy with respect to the given parameters. The constraints require the algorithm being fully automated while also being delivered by April 25, 2019.

The key feature of this algorithm is the moving average used to calculate the  $y_L$ ,  $y_H$ , and  $t_s$  values, which are used to calculate the  $\tau$  value. The algorithm then optimizes the statistical parameters to find the most accurate  $y_L$ ,  $y_H$ ,  $t_s$ , and  $\tau$ .

Three critical decisions were made in the creation of the parameter ID algorithm. The first algorithm design used a moving average method, while the second algorithm design noted consecutive positive or negative slopes. Both were tested and the first was found to be more reliable and accurate, as the first algorithm had a lower SSE value and matched the given temperature-based parameters more accurately. Therefore, it was decided early-on to discard the less reliable algorithm idea leaving the moving average algorithm as the clear choice.

After the first critical decision, the second iteration of the algorithm started at the end of the data and ran a loop in reverse until a certain number of consecutive changes in temperature were observed. Once the threshold was met, the algorithm traced back through the data to find the second temperature parameter. While the original idea was to move through the data left to right, the calculation was simplified by traveling right to left for the second parameter. It was decided that moving backwards through the data set was just as accurate as the original algorithm, however it was much more efficient to run the algorithm in this manner.

The last critical decision made regarded the use of threshold values. The algorithm was executed with varying threshold values to find the most accurate threshold for a specific data set, rather than have an arbitrary threshold that does not adapt to each data set. This minimized the error in determining parameter values returned by the algorithm. The modified SSE value of the model decreased significantly, and the  $r^2$  value was raised to 0.97 (See Table 2).

## **Algorithm Procedure**

### *Finding min and max temp ( $y_L$ and $y_H$ ):*

The initial temperature ( $y_H$  - cooling,  $y_L$  - heating) is the temperature right before the rise (heating) or fall (cooling). This data point shares the same index as  $t_s$ . The temperatures ( $y_L$  - cooling,  $y_H$  - heating) are computed by reversing the moving average method by decrementing the index of the last five points by one in a loop structure. The algorithm can then determine the temperature right after the rise or fall in temperature.

### *Moving Average:*

Provided with the noisy data of the five thermocouple models, the algorithm uses the moving average method to determine the point where the temperature starts rising (heating) or falling (cooling). This is achieved by obtaining the average temperature of the first five data

points and comparing it with the next five data points, using a loop structure. The next five data points are obtained by shifting the previous five data points to the right by one index.

*Finding  $t_s$  and  $\tau$ :*

After a set number of increasing (heating) or decreasing (cooling) averages have been detected, the algorithm returns to the data point where the first consecutive slope was detected and designates that point in time as  $t_s$ . The algorithm then locates the data point nearest to the 63.2% point from  $y_L$  to  $y_H$  using a loop that increments from the first index until 63.2% is reached. The value of  $\tau$  is assigned as the difference between  $t_s$  and the 63.2% time.

*Parameter Optimization:*

The entire algorithm will be run 15 times, varying the moving average block size and the threshold value with each run to determine the optimal conditions that return the most accurate temperature-based parameters.

## **Results & Interpretation**

Table 1 shows the M4 algorithm and its calculated temperature parameters for heating and cooling data. These parameters are close to the known values, which are calibration data, indicating low SSE. Figure 1 displays the temperature vs.  $\tau$  data for each thermocouple, with the nonlinear regression model curve overlaid on the data. The model indicates higher prices for shorter and more consistent  $\tau$  values. Table 3 shows the mean and standard deviation for the time constants for each FOS design. The low standard deviation values for each design show that the thermocouples were consistent in their measurements.

The errors that were encountered in the process were mostly caused by unsuitable threshold values for the noisy data, and the second algorithm returning inaccurate temperature-based parameters. The experimental data were of mediocre quality as it provided  $\tau$  values that were widely spread at each price level. Some of the price levels appear to have  $\tau$  values that are outliers. Errors in the algorithm can be further improved with an extension on the project and more research into an algorithm with absolutely no threshold. Despite the limitation, the algorithm is of high quality, which is evidently reflected by the rather low SSE value and very high  $r^2$  value of 0.97 (See Table 2).

FOS can say that their products are consistent and reliable enough for normal usage. The lower-priced thermocouples, as expected, had higher data variability than the higher-priced ones. Regarding pricing, models FOS-1 and FOS-3 are slightly overpriced, FOS-2 is underpriced, and FOS-4 and -5 are appropriately priced for their respective  $\tau$  values. While there were a few outliers for  $\tau$  measurement, these were few enough that the manufacturing consistency should not be questioned.

## **REFERENCE LIST:**

- Simple Linear Regression Slope Calculation. (2016, August 27). Retrieved March 21, 2019, from <https://www.mathworks.com/matlabcentral/answers/301079-simple-linear-regression-slope-calculation>
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Table 1. Parameter ID results with calibration data

Param	Unit	HEATING		COOLING	
		Clean	Noisy	Clean	Noisy
$t_s$	[sec]	1.5	1.5	1.5	1.42
Tau	[sec]	0.31	1.56	1.79	1.15
$y_L$	[°F]	0	-0.54	0.95	-0.4
$y_h$	[°F]	100	97.93	100	99.1s8

Table 2. Parameter ID regression

M4 Results	
Function Type	Exponential
SSE	91.05
SST	3071.13
$r^2$	0.97
Best-Fit Equation	Price = $-0.982 * (10 ^ { (20.836 * \text{Tau})})$

Table 3. Tau characteristics by thermocouple model

Model Number	$\tau$ Characteristics		Mean SSE <sub>mod</sub> [°F <sup>2</sup> ]
	Mean [sec]	Standard Deviation [sec]	
FOS-1	0.149	0.0312	0.3995
FOS-2	0.340	0.0367	0.4195
FOS-3	0.875	0.0523	0.4897
FOS-4	1.025	0.0784	0.5500
FOS-5	1.482	0.1103	0.6983

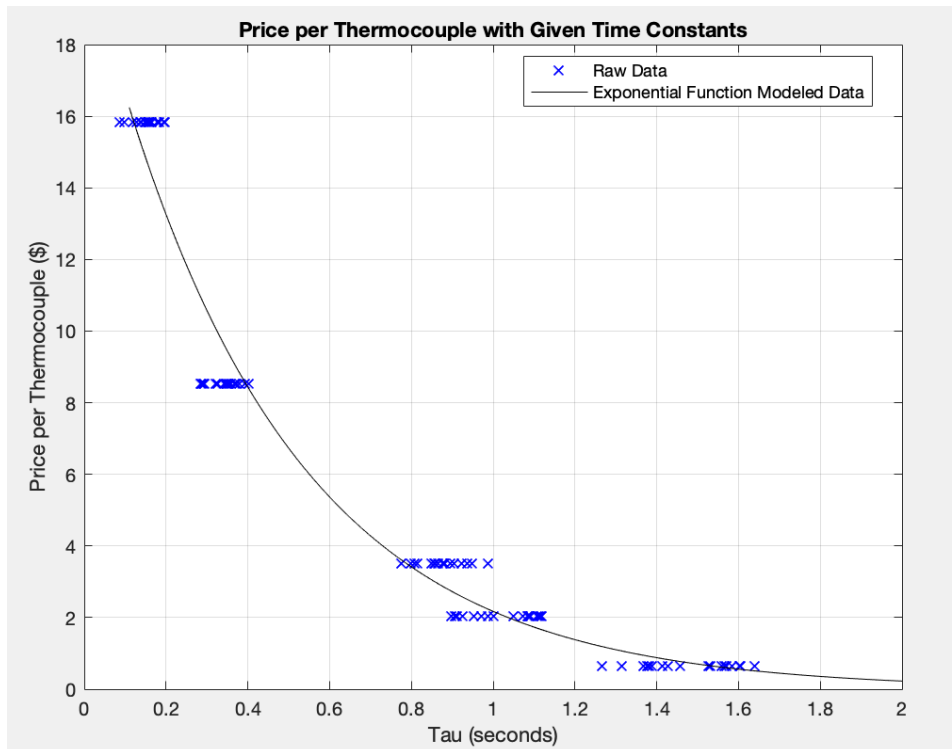


Figure 1. Tau Values per thermocouple model with regression plot