



# Modeling a Bioprinter

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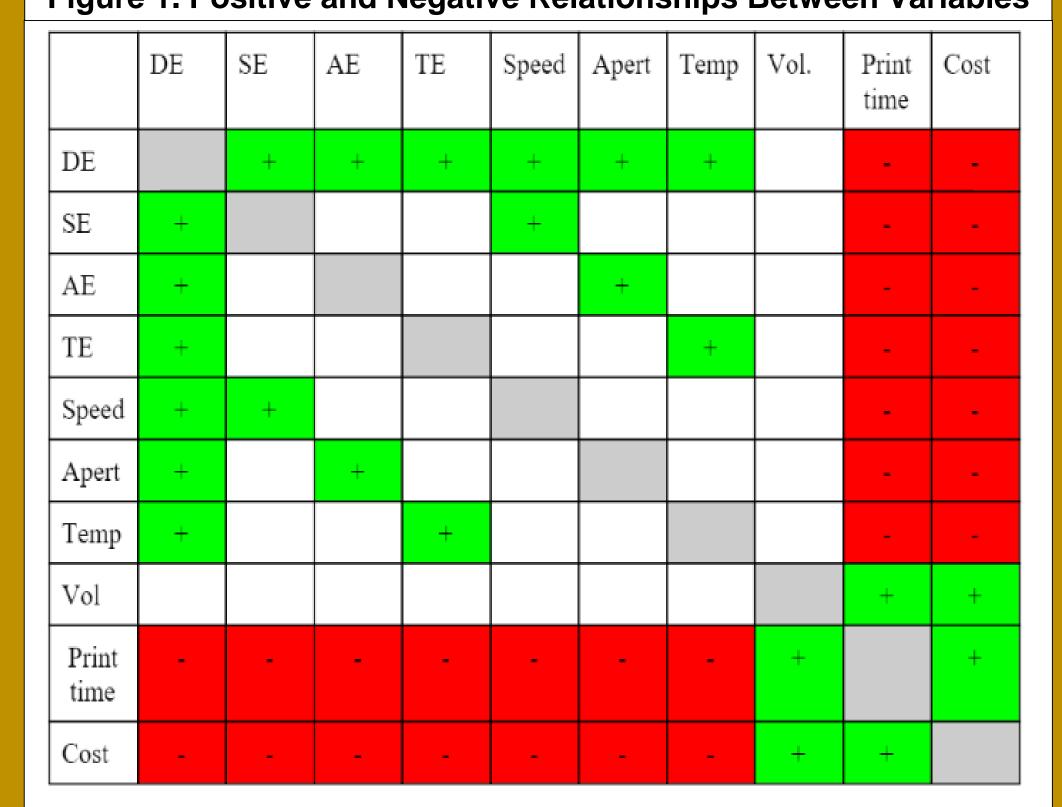




### Introduction

- Bio-printing is a new subset of 3D printing that uses biomaterials to create parts for use in medicine.
- The National Institute of Health (NIH) is funding companies to model a bio-printer in order to optimize its functions while reducing its cost.
- Potential parts include cartilage, tracheal splints, aortic valves, vasculatures, and kidneys.
- Each part has a different volume and tolerance for dimensional error that must be accounted for in the optimization of the bio-printer.
- A mathematical model of the performance of the bioprinter, using data provided by the NIH, as well as recommend a Factor of Safety for the bio-printer's use, was created to optimize the bio-printer.
- The model must find the optimal printer head speed, print aperture, and culture temperature, as well as an approximate dimensional error, production time, cost, and additional cost due to the Factor of Safety.

Figure 1. Positive and Negative Relationships Between Variables



## Methods

- AAMC first identified the variables that would affect the cost of operation, as well as the **relationships** between the variables (see Figure 1).
- The data obtained from the NIH was then cleaned based on experimental notes provided with the data.
- The cleaned data was then **modeled in graphs** to find the relationships between variables. Regression lines were developed with the Method of Least Squares, utilizing Microsoft Excel for non-linear models. (See Figures 2, 3, and 4).
- Using this data, a **mathematical model** of the bio-printer performance was created in Python 3.
- By analyzing the **goodness of fit** of the models of the experimental data, as well as taking into account external factors, a recommended Factor of Safety for each part was determined.

# Experimental Data

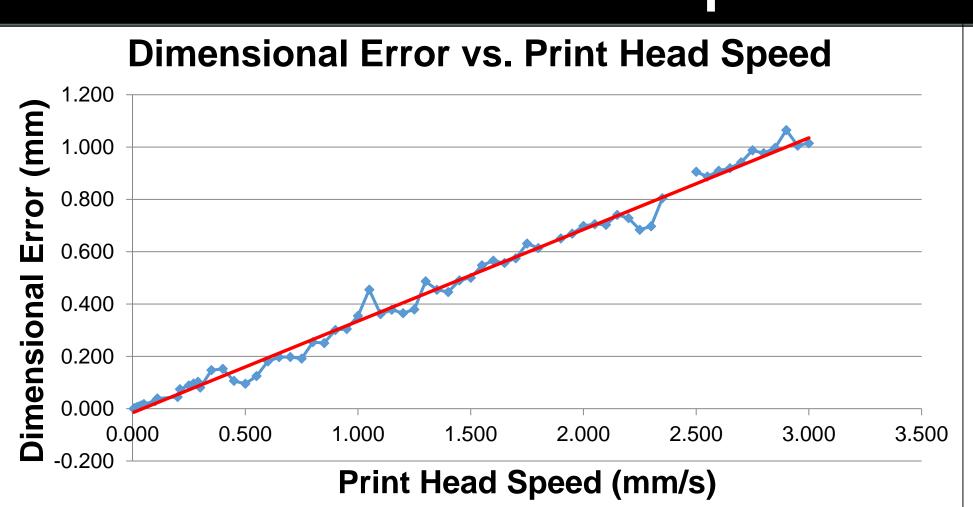
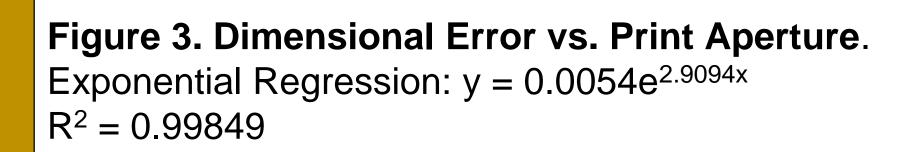
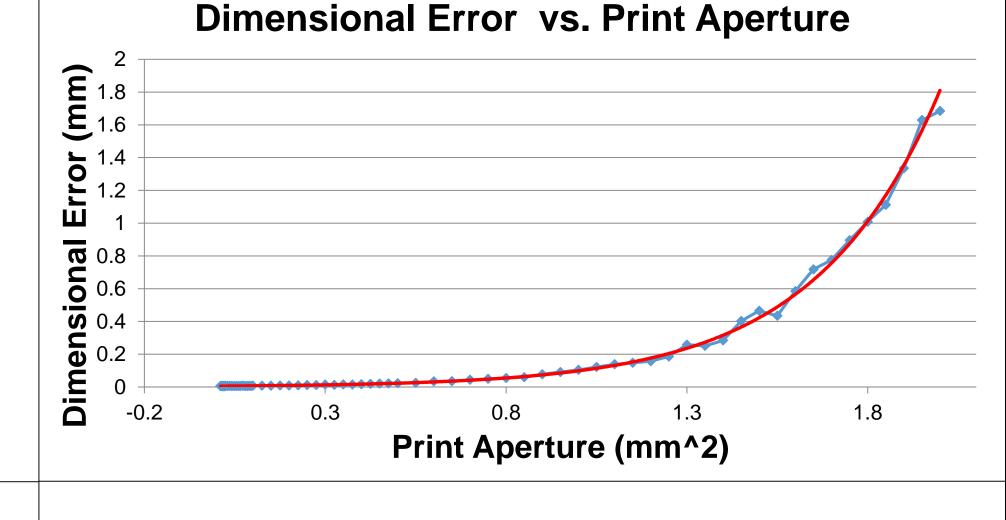


Figure 2. Dimensional Error vs. Print Head Speed. Linear Regression: y = 0.34224x $R^2 = 0.99002$ 





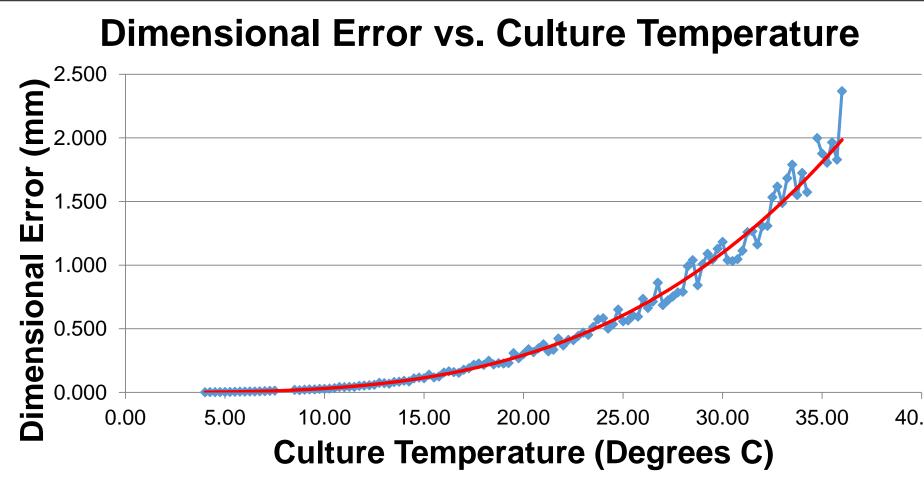


Figure 4. Dimensional Error vs. Culture Temperature Power Regression:  $y = 0.00002x^{3.2563}$  $R^2 = 0.99804$ 

### Results

- The model receives inputs of part volume, tolerance, and Factor of Safety from a user.
- An estimated dimensional error is found based on the Factor of Safety and part tolerance.
- The **regression lines** are determined based on the cleaned, imported NIH data.
- Values for the printer head speed, print aperture, and culture temperature are found with respect to the Factor of Safety, as well as the original part tolerance.
- **Printing** and **cure times** are found for both situations (with and without respect to the Factor of Safety).
- Respective **production times** for the part are then found.
- The **cost of production** is calculated with and without the Factor of Safety taken into account.
- The difference in cost between the two situations is found.
- The program outputs the optimal print head speed, print aperture, culture temperature, and the approximate production time, dimensional error, added cost due to Factor of Safety, and the total cost for the part production. (See Figure 5)
- The Factors of Safety that were determined for each part that the bio-printer will produce are as follows:
  - Cartilage: 189% Tracheal Splints: 325% Aortic Valves: 189%
  - Vasculature: 325% Kidney: 745%

#### Figure 5. Example Program Output

The optimal head speed for the desired part in mm/min is 35.29865.

The optimal print aperture for the desired part in mm^2 is 1.24376.

The optimal culture temperature for the desired part in degrees Celsius is 16.95431.

The production time for the desired part in minutes is 2183.

The estimated dimensional error for the desired part in mm is 0.20134.

The added cost due to the factor of safety for the desired part is \$ 35587.14.

The total cost for the desired part is \$ 86809.33.

# Factor of Safety

To determine the Factor of Safety, the following factors were taken into account in the calculations:

**Accuracy** of the Regression Models Ratio of Part Volume to Part Tolerance Unforeseen External Factors

- The average R<sup>2</sup> value for the regression models is 0.99552.
- This means that the model cannot account for 0.448% of the experimental error from the known factors.
- The ratios of part volume to part tolerance can be found in Table
- The **higher the ratio** between the volume and the part tolerance, the higher the factor of safety must be.
- These ratios were made into proportions based on the other ratios, as seen in Table 1
- Unforeseen external factors will be accounted for by including an additional 30% of the Factor of Safety calculated from the foreseen error.
- The formula for the Factor of Safety is [1 + (0.45)(Proportion)] \* (1.3) \* (100%)

Table 1. Determining Factor of Safety Data					
Part	Ratio (mm <sup>3</sup> /mm)	Proportion			
Cartilage	6,000	1			
Tracheal Splint	20,000	3.33			
Aortic Valve	6,000	1			
Vasculature	20,000	3.33			
Kidney	63,333.33	10.56			

#### Table 2. Program Outputs

Part	Head Speed	Aperture	Temperature	
Cartilage	46.38 mm/min	1.34 mm <sup>2</sup>	18.44 °C	
Tracheal Splint	2.70 mm/min	0.36 mm <sup>2</sup>	7.70 °C	
Aortic Valve	23.19 mm/min	1.10 mm <sup>2</sup>	14.90 °C	
Vasculature	13.49 mm/min	0.91 mm <sup>2</sup>	12.62 °C	
Kidney	35.30 mm/min	1.24 mm <sup>2</sup>	16.95 °C	

#### **Table 3. Program Outputs Continued**

Part	Production Time	Dimensional Error	Added Cost	Total Cost
Cartilage	105 min	0.26 mm	\$272.17	\$3392.78
Tracheal Splint	10322 min	0.02 mm	\$158,609.34	\$190,812.43
Aortic Valve	125 min	0.13 mm	\$336.74	\$3,006.37
Vasculature	426 min	0.08 mm	\$5749.59	\$10,169.23
Kidney	2183 min	0.20 mm	\$35,587.14	\$86,809.33

#### Conclusion

- Part prices can range from a few thousand to a couple hundred thousand based on the accuracy required and size of the part.
- These **recommended settings** ensure that parts will be within specification, but as inexpensive as possible.

# Acknowledgements

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