Large Deformation Patterns of 2D Mechanical Metamaterials

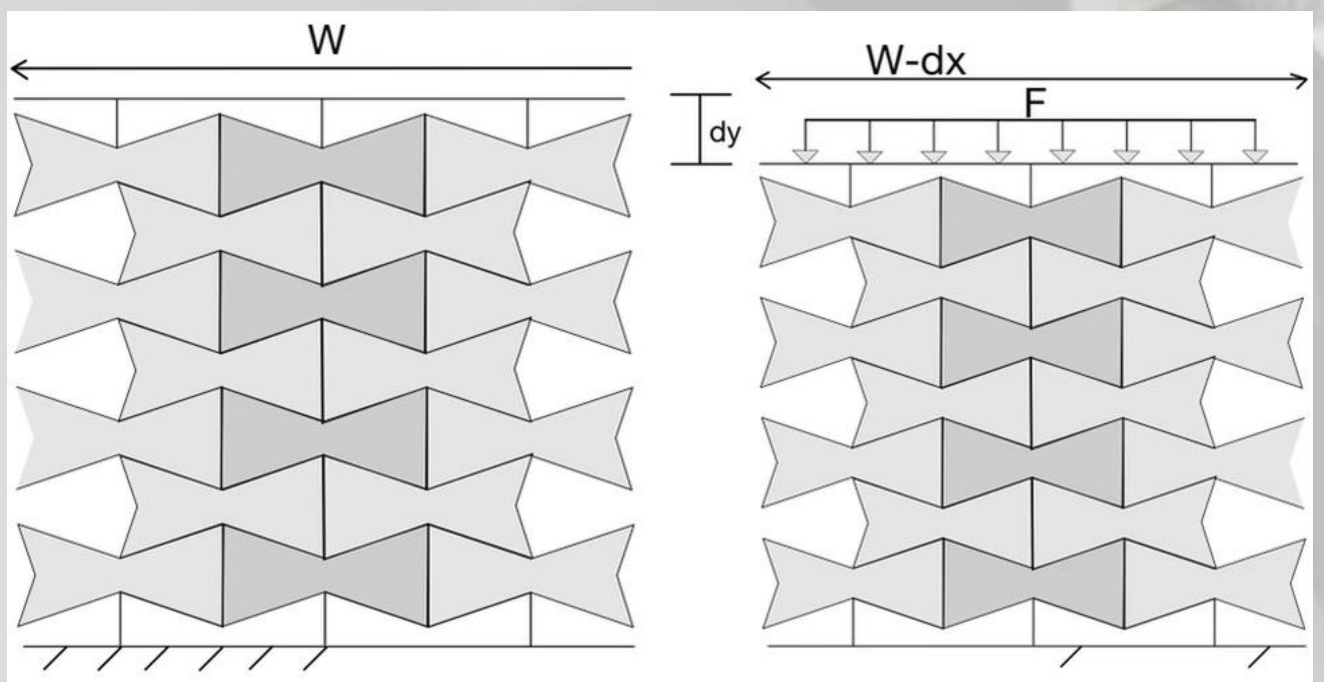
Department of Mechanical Engineering, The University of Utah

Group 2: Nolan Strauss, Jake Hirst, Jake Schauer, Zane Kincaid, Jonas Merrell
Advisor: Pai Wang

Intro

Metamaterials have limitless potential and applications. They are composites that exhibit properties that do not occur naturally. Mechanical metamaterials are metamaterials that exhibit non-natural properties based solely on their geometry. Recently, new classes of metamaterials including shape morphing metamaterials have exhibited functionalities in response to mechanical forces. This project is meant to exploit the functionalities of metamaterials in order to make them useful for real world applications

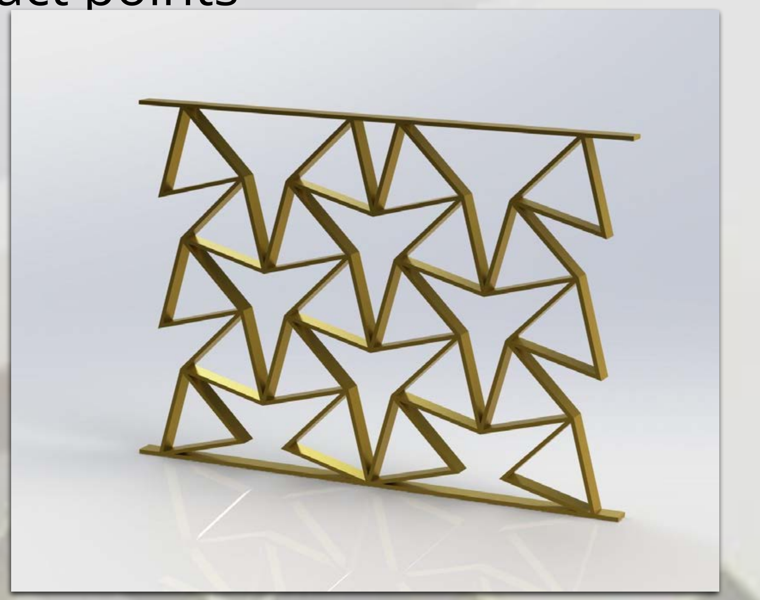
The Overarching goal of this year-long project was to create a computational model that generates a metamaterial that exhibits unique properties inputted by a customer. Our team focused on creating a computational model that will generate a metamaterial with a customer's desired poisson's ratio. To do this, we also incorporated our own design into the metamaterial that we call Delayed Contact Points (DCP). These DCP's are small bits of material strategically placed throughout the geometry. When compressed, the DCP's will contact each other at different iterations of the displacement process, thereby manipulating the poisson's ratio.



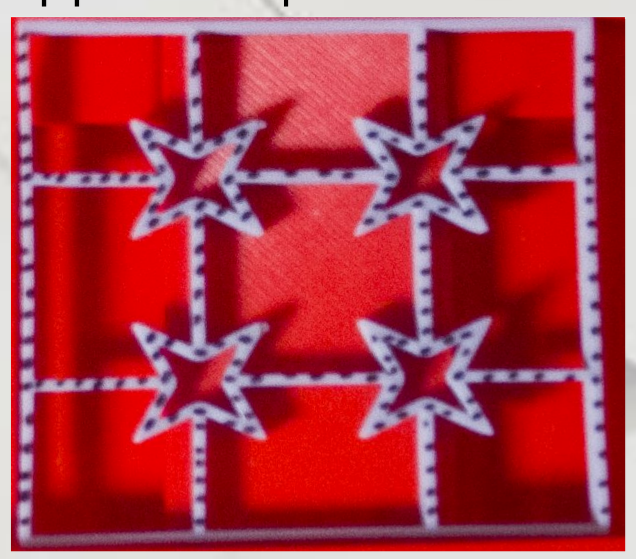
Problem: Mechanical Metamaterials (MM) have shown promising attributes that may be applied and used within new products. Unfortunately, the application of MM within products are limited by the developers ability to manipulate the needed properties.

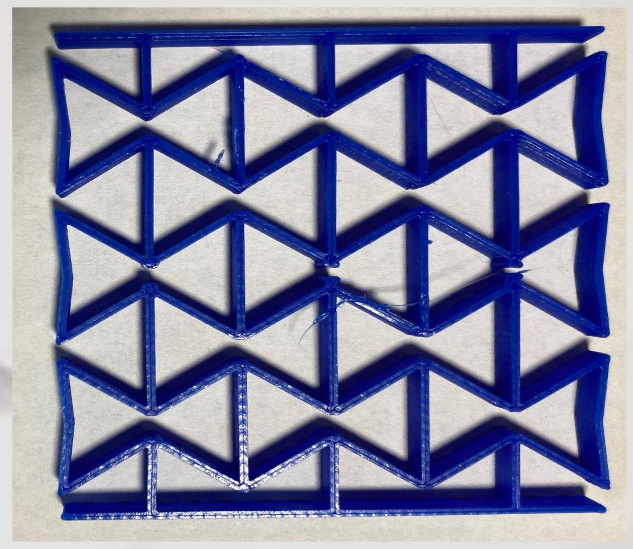
Methods

1. **Development of 2D Mechanical Metamaterials (MM)**
   a. Delayed contact points



2. **Creation of physical 2D Mechanical Metamaterials (PMM) and 2D Mechanical Metamaterial Computational Models (CMM).**
   a. 3D printed PMM models and test jig to apply displacement
   b. Created CMM models using ABAQUS finite element analysis software
3. **Testing of PMM and CMM.**
   a. Tested PMM using a 3D printed test jig to apply displacement to PMM. Dots were drawn at different spots on the PMM to measure displacement and calculate Poisson ratio
   b. ABAQUS finite element analysis software used to simulate an applied displacement and calculate Poisson ratio





4. **Data retrieval of CMM for Machine Learning Program (MLP) development.**
   a. Vertical strains, delta values, and poisson ratio were stores.
   b. An interpretable Machine Learning (ML) method was chosen over a black-box method such that models could be understandable for users.
   c. The interpretable ML method chosen was Genetic Programming by Symbolic Regression (GPSR).
   d. GPSR was performed via Bingo, a GPSR Python package developed at the NASA Langley Research Center (LARC).
   e. Vertical strains and delta values are inputs to MLP and the poisson ratio is the output.
   f. MLP is highly influenced by training data and ML hyperparameters.
5. **Comparison of PMM with experimentally found data.**

Results

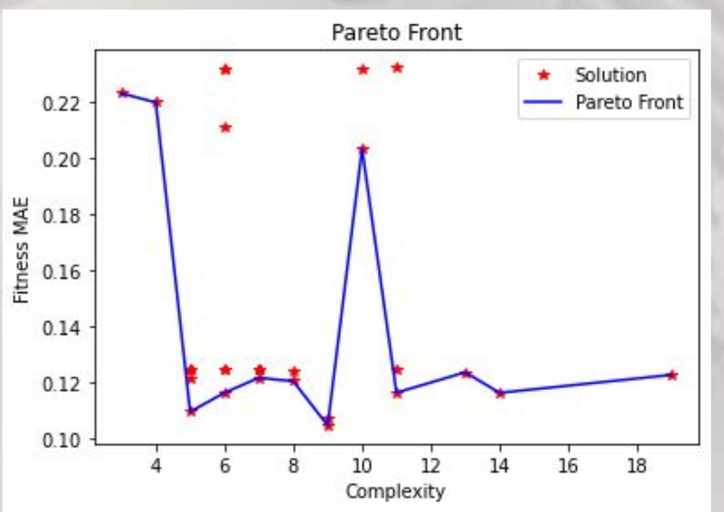
After the determination of a novel metamaterial that expressed a non-linear poisson ratio response to an applied vertical displacement, PMMs and CMMs with varying delayed contact deltas were created and evaluated. Upon evaluation of the CMMs, the poisson ratio, vertical displacement, and delta values were recovered and stored. This stored data was then used with Bingo and the following model was developed.

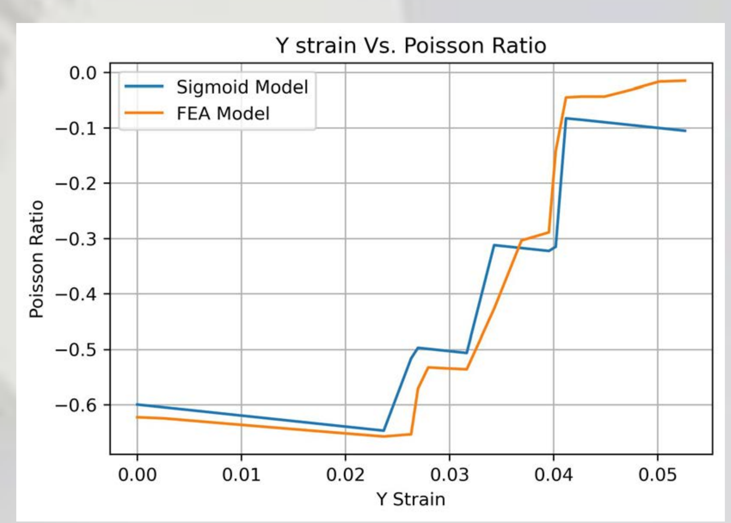
$$\nu = -2\varepsilon_y - 0.6 * \sum_{t=1}^{3} c_{di} S_i(\varepsilon_y)$$

The components of this equation are explained by the following relations.

$$S_i(\varepsilon_y) = \frac{1}{1 + e^{-k(\varepsilon_y + (\frac{c_{di}}{10}))}} \quad c_{di} = \frac{di}{\sum_{i=1}^{3} di}$$

This model showed to give us a mean absolute error of 4.65% with respect to unseen data. Below are two plots, one showing the pareto front, a plot useful to help users determine the best model from GPSR (left) and a plot of the previously stated equation ability to predict trends in unseen data.





FInally, FEA models were validated by compressing our models with our testing jig, and ensuring the MAE between our physical and FEA models is reasonable.

Conclusion

Creating computational models for mechanical metamaterials is not an easy task, but it is possible. The shown example of predicting a specified material response shows promising potential to the further development of this field.