

# Hybrid Machine Learning Characterization and Parameter Space Analysis using Interactive Visualization for Analyzing the Quality of Virtual Nonwovens



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**Viny Saajan Victor**  
*Department of Computer Science*

Supervisors: **Prof. Dr. Heike Leitte, Dr. Andre Schmeißer**  
*Technische Universität Kaiserslautern, Germany*  
*Fraunhofer ITWM, Kaiserslautern, Germany*

# Simulating Production Process and Virtual Production of Nonwovens

## **Fiber Dynamics Simulation Tool (Fraunhofer ITWM):**

- simulates fibers in turbulent flows.

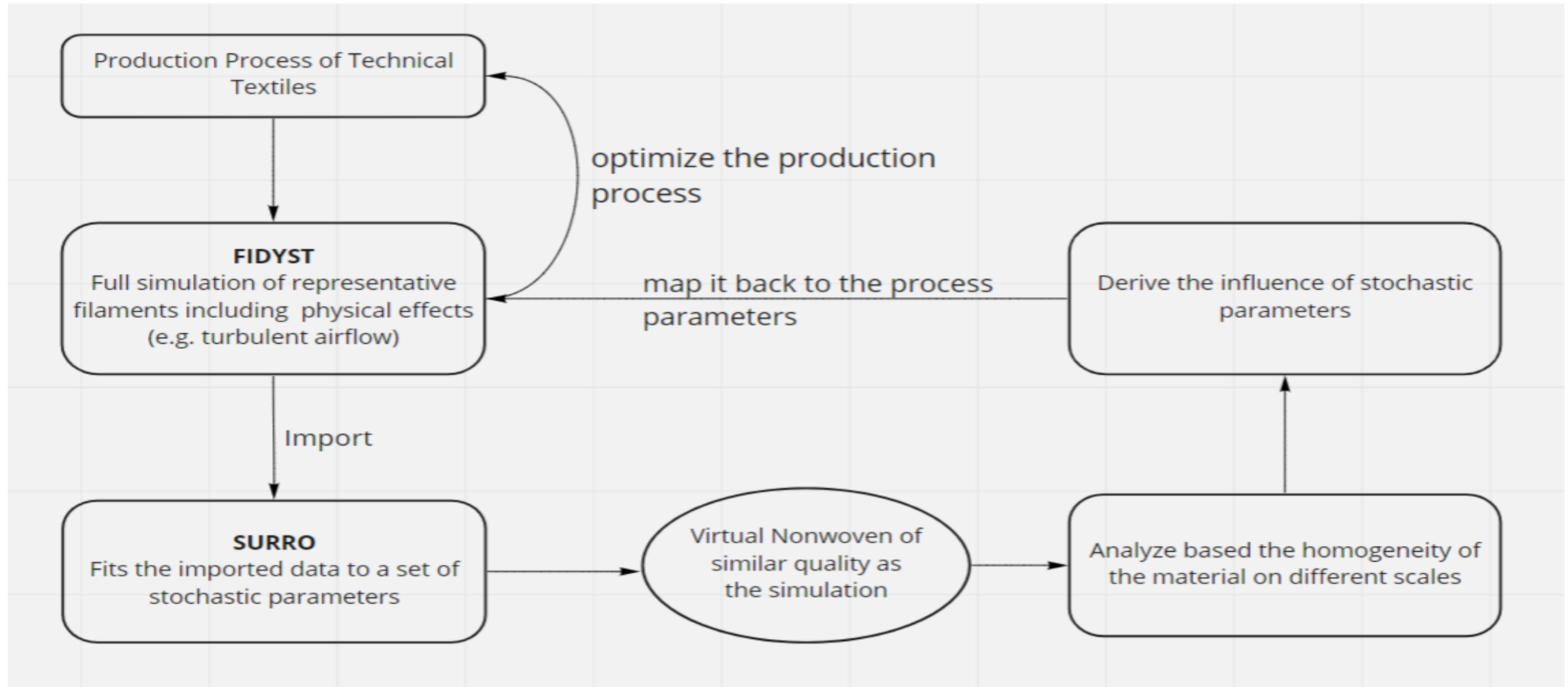
## **Software Surro (Fraunhofer ITWM):**

- generates large-scale virtual nonwoven structures.
- mathematical defined by stochastic differential equation.

## **Purpose:**

- used to optimize the geometry of production plant and operating conditions.
- improve product quality, reduced energy and raw material consumption.

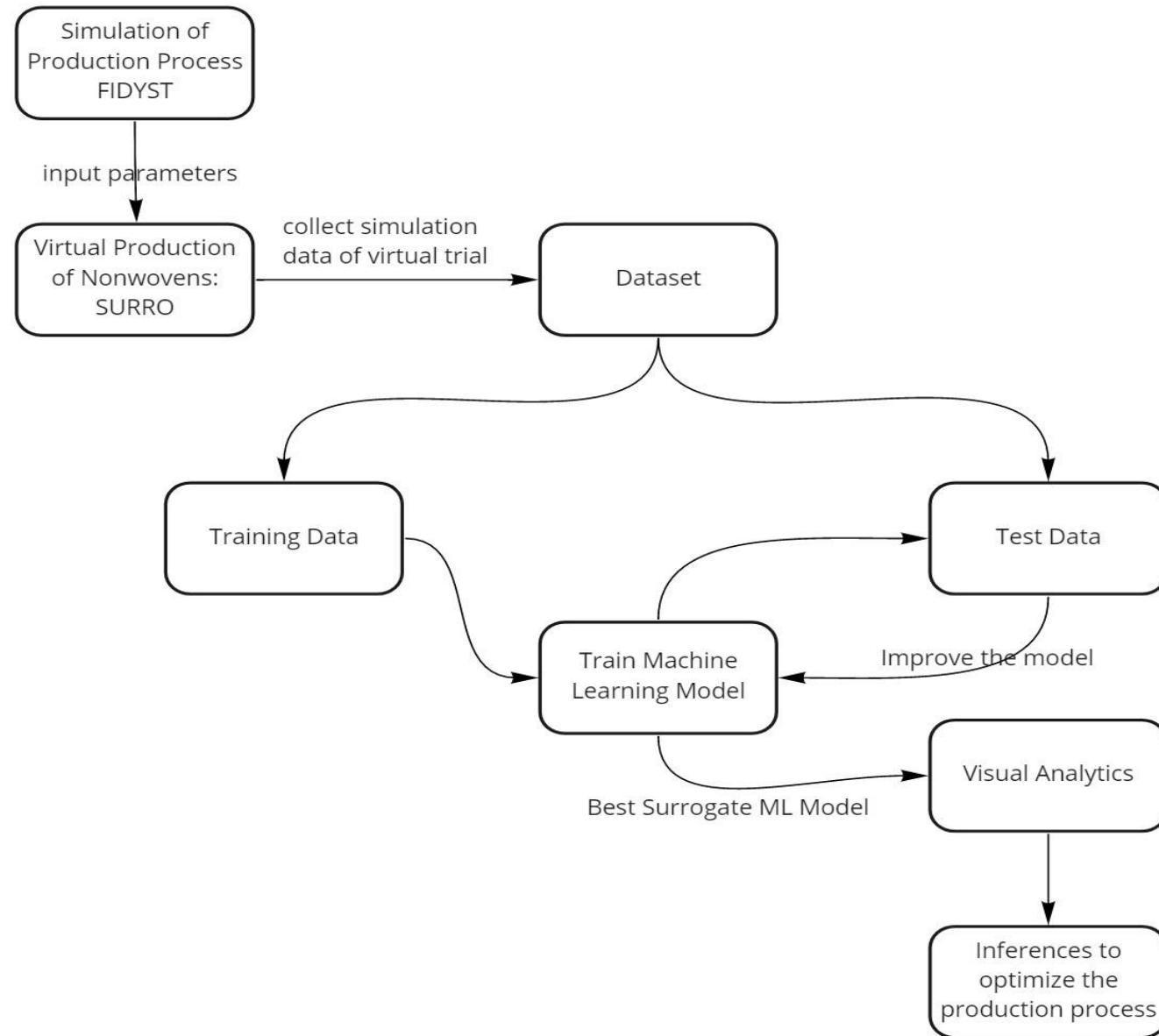
# Analysis of Nonwoven production processes using FIDYST and SURRO



# Motivation

- **Reduce the computation time and resources:**
  - virtual production of large nonwovens consumes more time and resources.
  - require a model that maps the stochastic parameters to the product quality in real time.
- **Visual assistance in analyzing the quality of the nonwovens:**
  - require visual interface which helps the use in parameter space analysis for finding the desired quality of the end product.
  - helps the user to understand the influence of process parameters on the product quality by analyzing in influence of the stochastic parameters.

# Thesis Structure



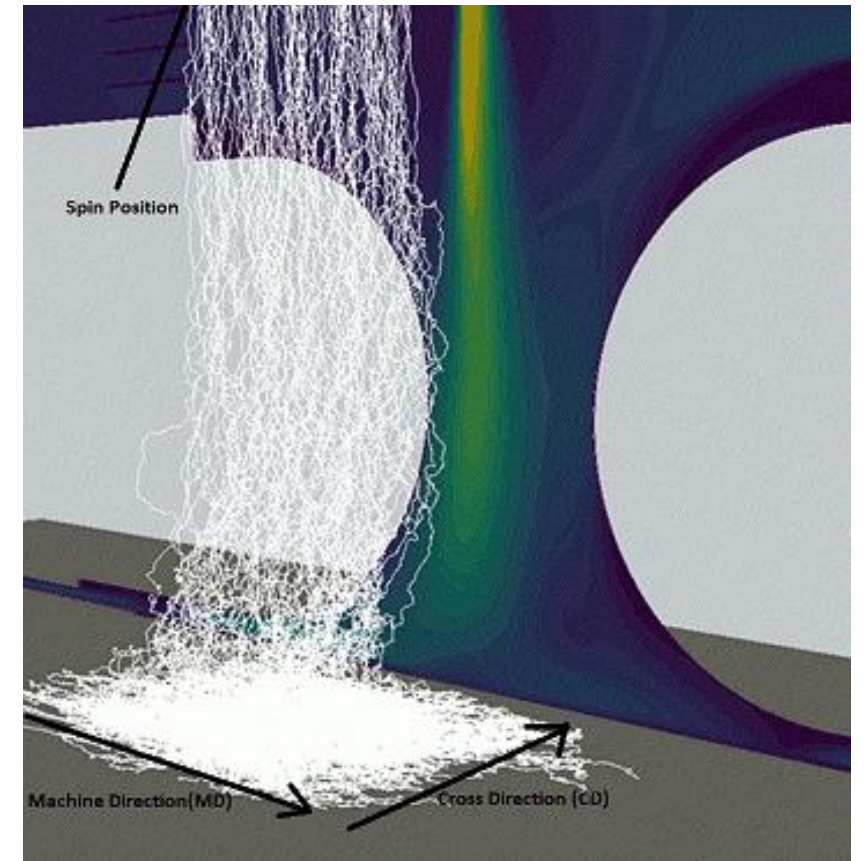
# Input and output features for Machine Learning Models

## Input Features:

- Sigma\_1 : standard deviation of normal distribution of fiber position in machine direction without the belt movement, range: [1-50].
- Sigma\_2 : standard deviation of normal distribution of fiber position in cross direction without the belt movement, range: [1-50].
- A : random effects of the production process (eg. Influence of turbulent flow , fiber-fiber contacts etc), range: [1-50].
- BeltSpinRatio : ratio of spinning speed and belt speed, range: [0.01-0.25].
- SpinPositionsPerMeter : number of spin positions per meter, range: [200-10000].

## Output Features:

Coefficient of Variation(CV): Std/Mean : homogeneity : at 7 resolutions.



# Nonwoven Sample Simulation Setup

## **Sample Region Size Selection**

Purpose:

- reduce the computation time and memory.
- only simulate the fibers that overlap with sample region.

Selected region sizes:

5cm\*5cm, 15cm\*50cm, 25cm\*50cm : Evaluated with the initial database with 3125 rows.

Inferences:

- Larger the region size -> Lesser the statistical uncertainty.
- Sampling the same parameter setting multiple times reduces the uncertainty.

Choice Made: Sample region size : 25cm\*50cm, Number of runs: 5

# Nonwoven Sample Simulation Setup

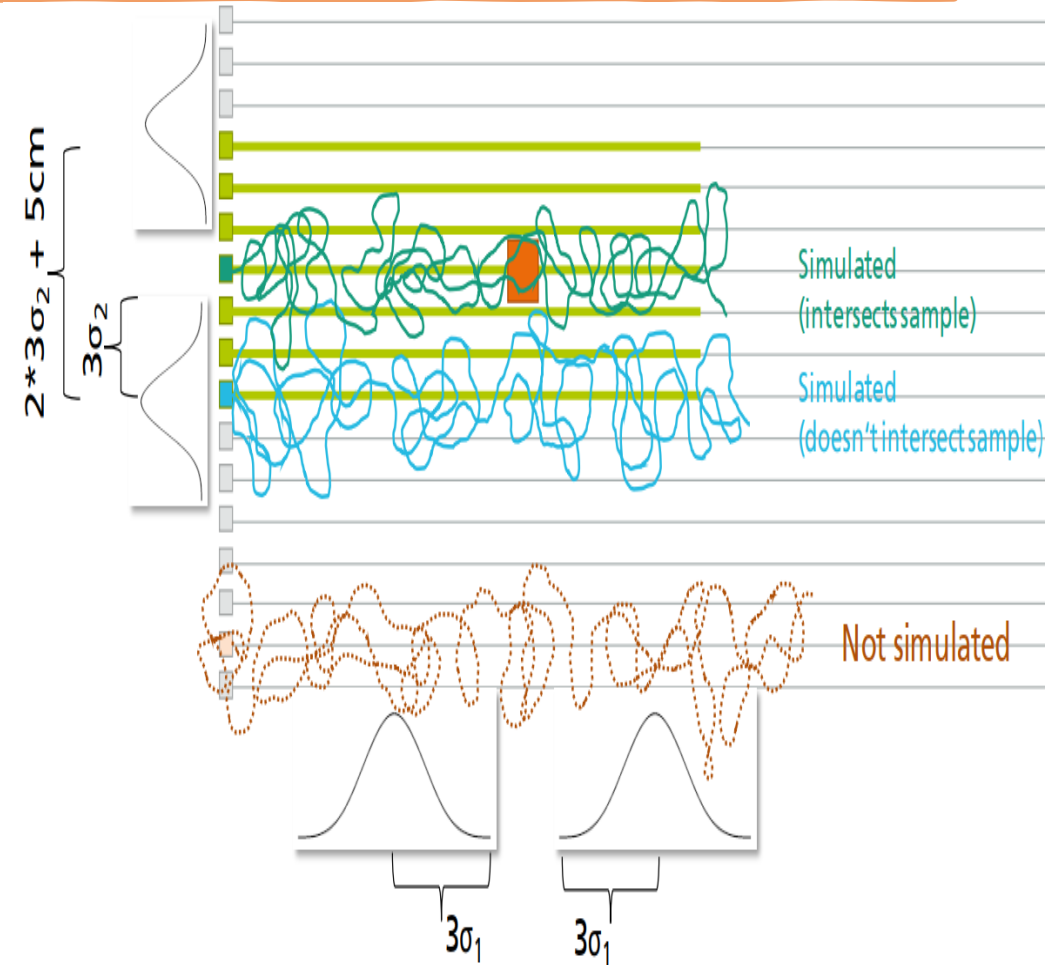
## Construction of Nonwoven samples based on Sample Size

Values lies with 2, 2.5 and 3 std away from mean in normal distribution are 95%, 99% and 99.7%.

Hence we simulate:

$[2.5\sigma_2 - 3\sigma_2]$  of nonwoven in cross direction around sample region.

Bit more than  $3\sigma_1$  in machine direction around sample region





# Dataset Creation

## Input Database

- smaller number of inputs on a lattice, add additional randomly distributed inputs.
- 50,000 Latin Hypercube Samples(LHS) : distributes samples evenly over sample space.
- 12348 combination of discrete samples.
- total number of rows =  $(50,000+12348)*5 = 311740$

## Output Database:

- Input rows + CV values at 7 resolutions.
- Divided the input data into 16 batches of 20,000 rows and ran the simulations.

	Sigma_1	Sigma_2	A	BeltSpinRatio	SpinPositionsPerMeterInverse	RandomSeeds
0	1.000000	1.000000	1.000000	0.010000	200.000000	[1213095470, 442944496, 634841805]
1	1.000000	1.000000	1.000000	0.010000	200.000000	[1642774584, 414207576, 1611613430]
2	1.000000	1.000000	1.000000	0.010000	200.000000	[1248361643, 518153081, 1721992811]
3	1.000000	1.000000	1.000000	0.010000	200.000000	[1834129115, 952397124, 1184676440]
4	1.000000	1.000000	1.000000	0.010000	200.000000	[1274595782, 707387979, 1557540557]
...	...	...	...	...	...	...
311735	3.513361	20.232137	23.026302	0.180353	837.352405	[1003094736, 591635343, 1961093723]
311736	3.513361	20.232137	23.026302	0.180353	837.352405	[953213396, 1283929761, 639338037]
311737	3.513361	20.232137	23.026302	0.180353	837.352405	[538647705, 364740067, 1005850105]
311738	3.513361	20.232137	23.026302	0.180353	837.352405	[1442998392, 648729299, 2074783063]
311739	3.513361	20.232137	23.026302	0.180353	837.352405	[635667682, 806371089, 1143299561]

311740 rows × 6 columns

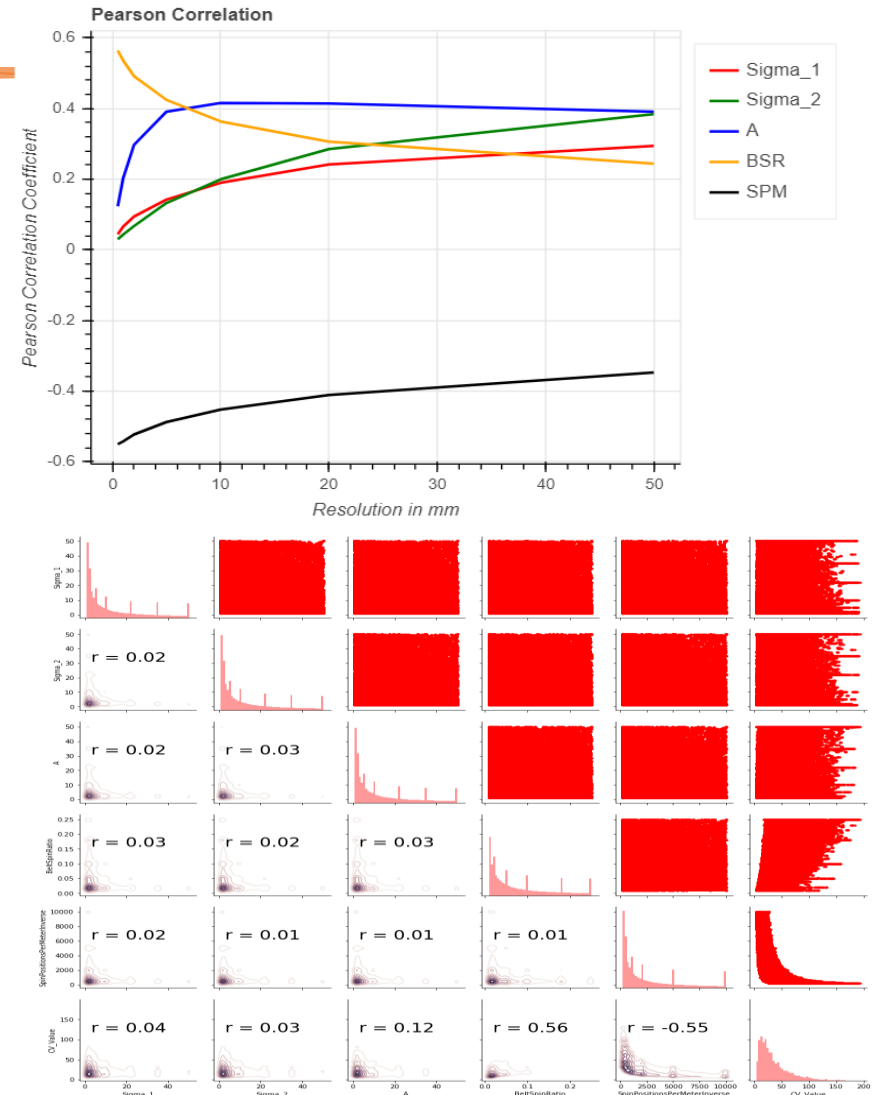
# Exploratory Data Analysis and Data Preperation

## EDA

- Pearson correlation between the input and output features.
- Pair plots for visualizing.
- Sigma\_1, Sigma\_2, A and BeltSpinRatio positively correlated and SpinPositionsPerMeter is negatively correlated to the output features.

## Data Preparation

- data cleaning : removal of random seeds.
- feature scaling: measurements of different units :  
standardizing the data(rescale with mean=0, and std=1)
- data splitting : training, validation and testing.



# Regression Models

## Problem setting

5 continuous/discrete input features used to predict 7 continuous output features.  
Multiple input, multiple output regression.

## Model selection criteria

accuracy, interpretability, scalability, confidence on predictions and application domain.

## Metrics used for evaluation

Mean Absolute Percentage Error(MAPE).

Mean Squared Error (MSE).

Co-efficient of Determination (R<sup>2</sup> Score).

$$MAPE = \left( \frac{1}{n} * \sum_{i=1}^n \frac{y_i - \hat{y}_i}{y_i} \right) * 100$$

$$MSE = \frac{1}{n} * \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

$$R^2(y, \hat{y}) = 1 - \left( \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \right)$$

Here,  $n$  refers to the number of data points,  $y_i$  and  $\hat{y}_i$  refer to the actual and predicted values respectively for the data point  $i$  and  $\bar{y}$  is the mean value of the data points.

# Regression Models

Regression Model	MAPE(%)	MSE	R2-Score
Multi-Linear Regression	94.57	94.55	0.60
Polynomial Regression (Degree = 9)	8.62	1.79	0.99
Random Forest Regression	9.84	1.81	0.98
Bayesian Polynomial Regression (Degree = 9)	7.72	1.51	0.98
Neural Network Regression	3.76	0.35	0.99

# Regression Models

## Neural Network Regression

- network of functions to understand and translate a data input to desired output .
- Hyper-parameter optimization for best Neural Network Architecture
  - \* Number of Hidden Layers = [1-5]
  - \* Number of nodes in each layer = [8-1024 with increment of 8]
  - \* Activation functions = [relu, sigmoid, tanh]

Resolution (in mm)	MAPE(%)	MSE	R2-Score
0.5	0.80	0.50	1.00
1	1.02	0.47	1.00
2	1.38	0.39	1.00
5	2.18	0.27	1.00
10	3.33	0.27	1.00
20	5.31	0.25	0.99
50	12.31	0.27	0.97
All	3.76	0.35	0.99

# Regression Models

## Neural Network Regression

- selected network architecture based on accuracy.
- selected activation function: relu

## Automated ML Analysis

- plug-and-play model for future integrations of novel unseen data, regression models, new evaluation metric etc.

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 256)	1536
dense_1 (Dense)	(None, 512)	131584
dense_2 (Dense)	(None, 512)	262656
dense_3 (Dense)	(None, 256)	131328
dense_4 (Dense)	(None, 768)	197376
dense_5 (Dense)	(None, 7)	5383
Total params: 729,863		
Trainable params: 729,863		
Non-trainable params: 0		

## ML\_Model\_Metrics.csv

Row: 4 Column: 34 Characters: 150

1	Regressor,MSE,R2_Score,MAPE(%)
2	Random Forest Regressor,1.81,0.98,9.84
3	Neural Network Regressor,0.35,0.99,3.76
4	Bayesian Regressor,1.51,0.98,7.72

# Visual Analytic Tool

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## Main Objectives

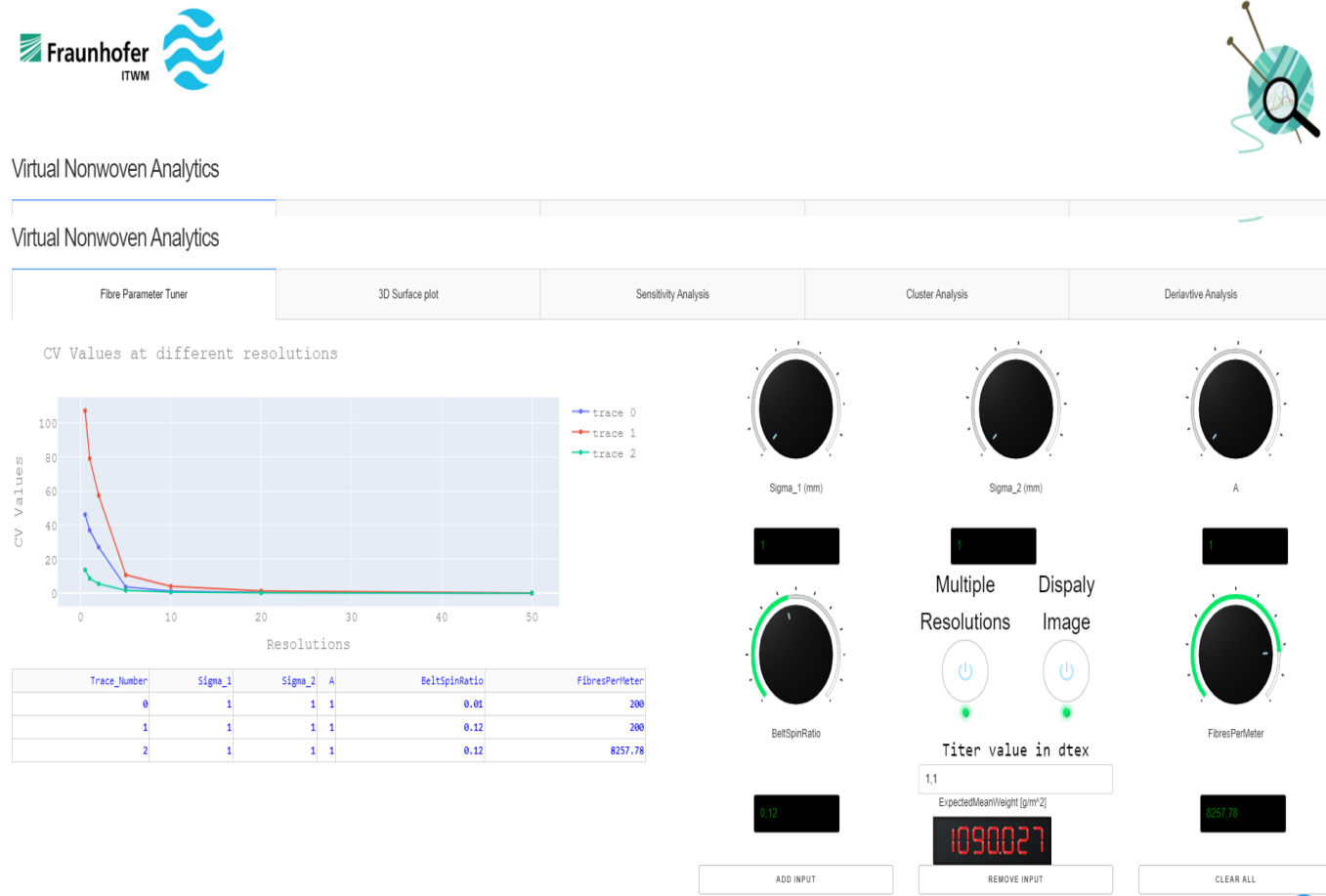
- understanding the relation between input and output parameters and the sensitivity of the output values to minor changes in the input parameters.
- visually aid the users to reach their optimal set of input parameters which result in the desired output.
- show patterns, clusters and anomalies in the data for better understanding of the data.
- data navigation in real-time.



# Visual Analytic Tool

## Parameter Tuner

- analysis of the output for all the res.
- comparison between more than one parameter setting (add, delete, clear).
- analysis of the output for individual resolutions over a range.
- expected mean weight calculation.  
Expected Mean Weight =  
 $\text{titer} * \text{SPM} * \text{BSR}$   
[titer->weight per unit length]





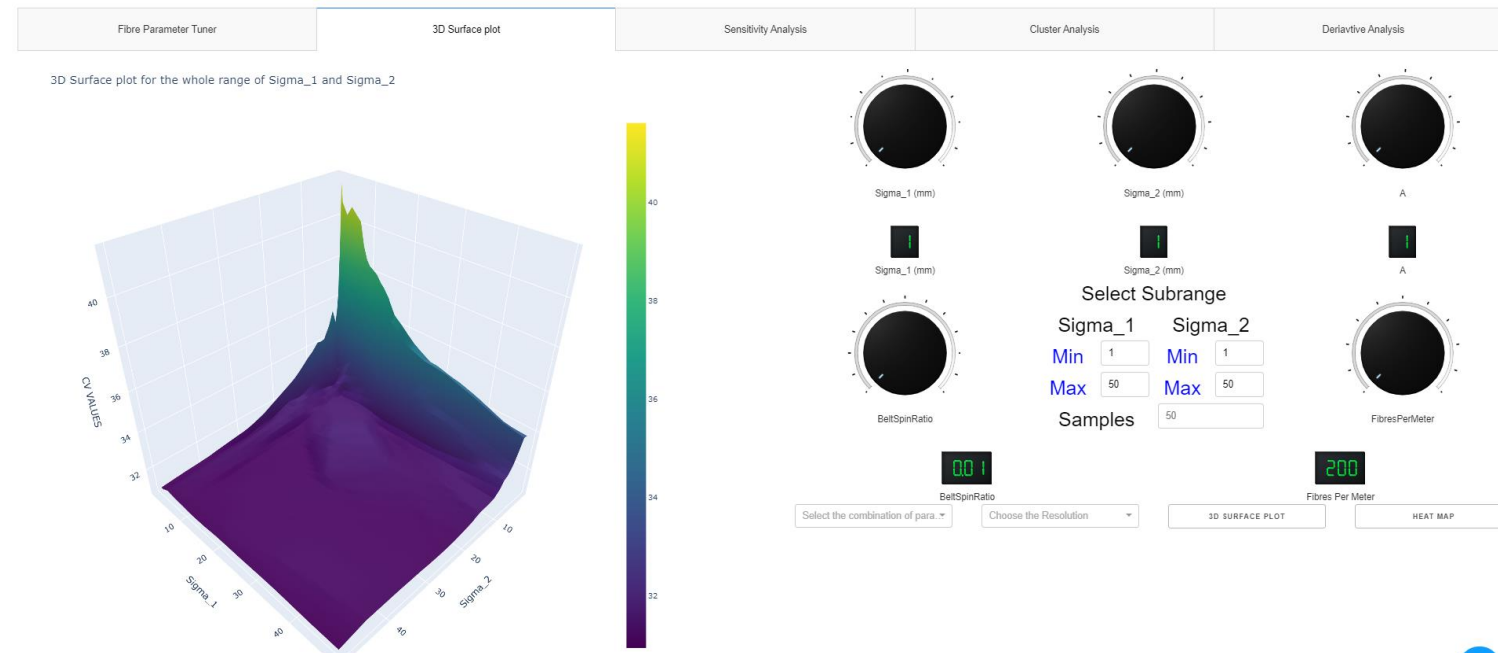
# Visual Analytic Tool

## 3D Surface Plot

- understanding the influence of input parameters by freezing combination of parameters.
- Dynamic update of the graph with 2500 values in real-time.
- Sub-range selection for "Details on Demand" Analysis.
- Analysis for individual resolutions.



Virtual Nonwoven Analytics



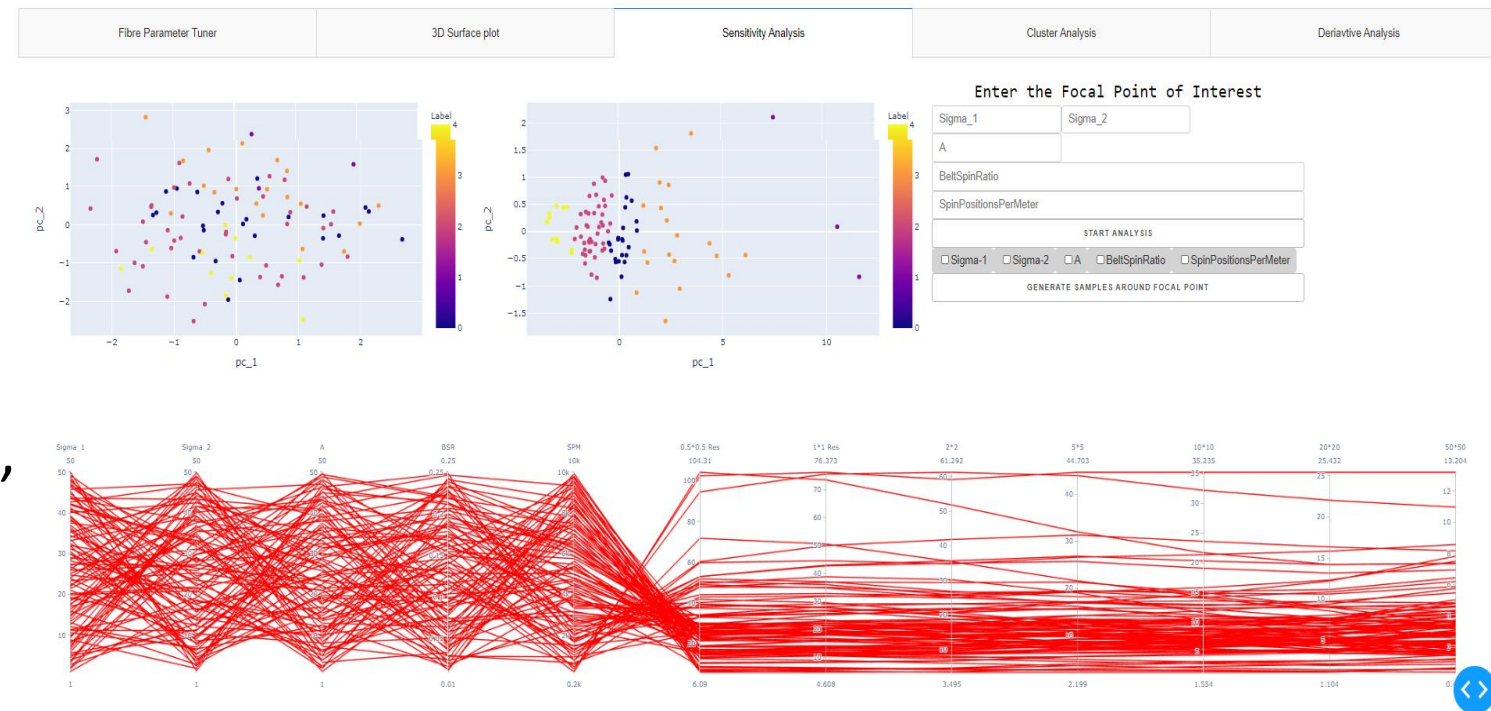
# Visual Analytic Tool

## Sensitivity Analysis

- to determine the robustness of the output values against small changes in the input parameter settings.
- components : input space graph, output space graph and parallel plot.



Virtual Nonwoven Analytics

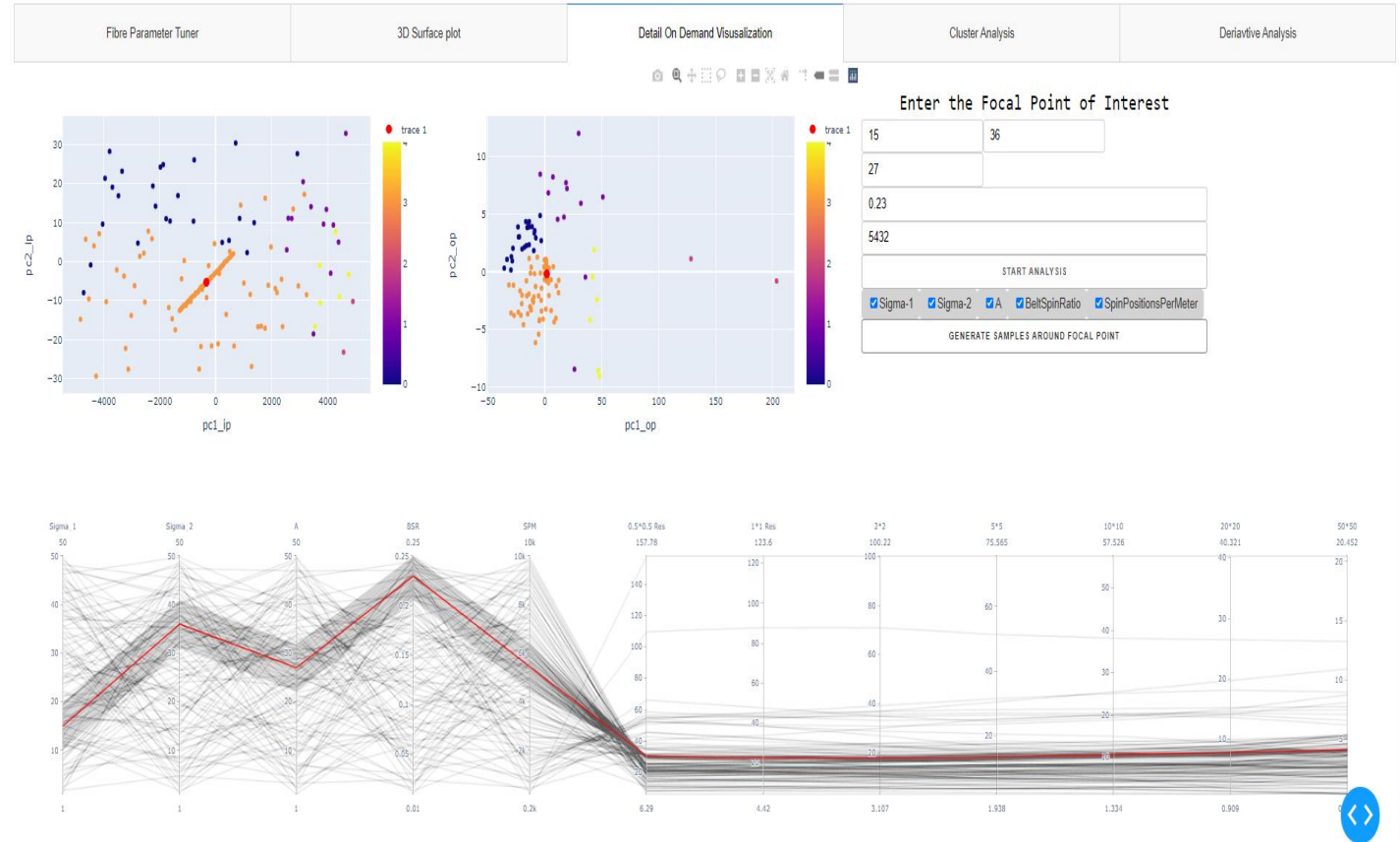


# Visual Analytic Tool

## Sensitivity Analysis

The Analysis:

- Selection of Focal Point
- Selection of area and population of local neighbourhood.
- Updating the local neighbourhood (local and global update).
- Apply changes on the components



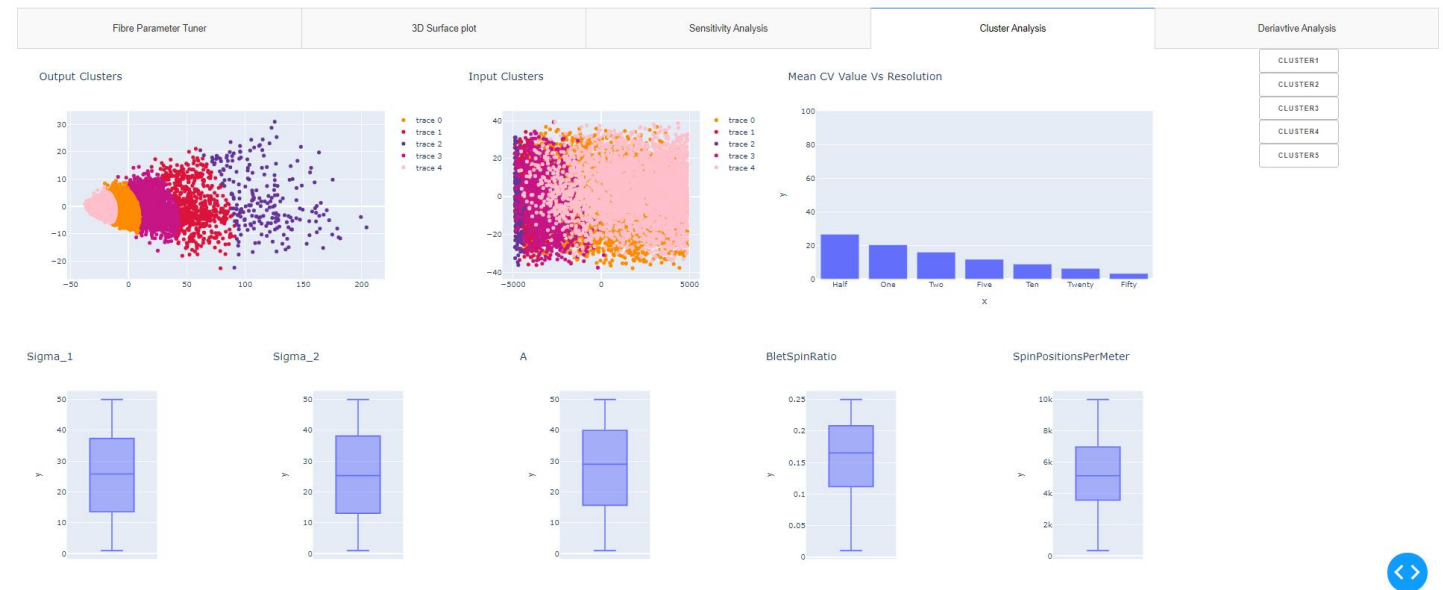
# Visual Analytic Tool

## Cluster Analysis:

- Partition of output dspace (PCA + GMM clustering).
- Assign a Quality Measure to the Partitioned Data (Average CV value).
- Mapping the partitions to the input space (Box-plot for analysing The distribution of input features).



Virtual Nonwoven Analytics



# Visual Analytic Tool

## Partial Derivative Analysis:

- partial derivatives of the output with respect to the chosen input at fixed points.
- central finite difference as an approximation for the partial derivatives.
- range slider for the user to select the region of interest.
- Analysis for individual resolutions.



# Inferences

- Optimal vs Non-sensitive Parameter Setting using sensitivity analysis.
- Desired resolutions for differentiating nonwovens:
  - \* higher resolutions do a better job in classifying nonwoven materials as "good" or "bad" compared to lower resolutions.
- Local minima in optimizing the process parameters.
- Outliers in Clusters.

# Future Scope

- Point out the exact resolution that differentiate the behaviour of the materials.
- Other metrics to differentiate between the clusters.
- Incorporate the confidence of the machine learning model in the tool using the Bayesian regression model.
- utilize the SURRO simulation images instead of CV values and train these images over a Convolutional Neural Networks to find a measure for determining the quality of the material.



THANK YOU