Object Shape Error Response (OSER) using Bayesian 3D Convolutional Neural Networks for Assembly Systems with Compliant Parts

Predicting and Preventing Manufacturing Defects

Presented by: Sumit Sinha
Sumit Sinha, Pasquale Franciosa, Dariusz Ceglarek

Digital Lifecycle Management (DLM)
WMG, University of Warwick, UK

WMG
THE UNIVERSITY OF WARWICK

Outline

1. Introduction

- Problem & motivation – *Background*
- Challenges & objectives – *Literature review*

2. Methodology: *Object Shape Error Response (OSER)*

- Object shape error estimation – *Transition from object detection to object shape error estimation*
- Framework – *Bayesian deep learning and CAE simulation integration*
- 3D CNN Architecture Optimization – *Extending traditional architectures used in object detection*
- Bayesian Deep Learning – *Uncertainty quantification*

3. Industrial case study: *Automotive door assembly process*

- Assembly system setup
- Results

4. Benchmarking and Discussion

- OSER vs. current *statistical models* used for Root Cause Analysis (RCA) in manufacturing
- OSER vs. current *machine learning* models **NOT** used for Root Cause Analysis (RCA) in manufacturing

5. Summary & Conclusions

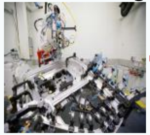
- Contributions & applications

Problem & Motivation

Problem: **Product quality → detection of geometric errors**

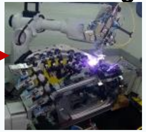
Multi-Stage Assembly Station

Positioning

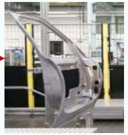


Clamping

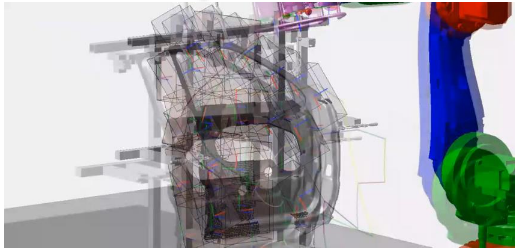
Fastening



Release



3D Optical Scanner



Quality requirements

Zero Defect Manufacturing

Right First Time

Shorten NPI lead time

Process Parameters (y):
(1) Locators; (2) Clamps; (3) joining

Root Causes (subset of y):
any of the process parameters out of nominal

Object point cloud data

Object Shape Error (x)

Challenges

- High resolution point cloud data
- Deformable Parts
- Fault Multiplicity for 6-sigma
- Costly corrective actions
- No samples at design stages

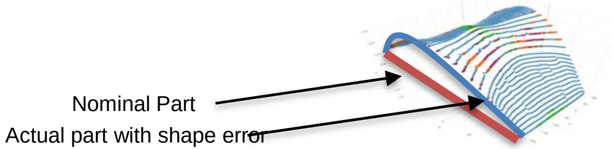
Goal: **Automated Root Cause Analysis (RCA) of geometric error during assembly**

Challenges & Objectives

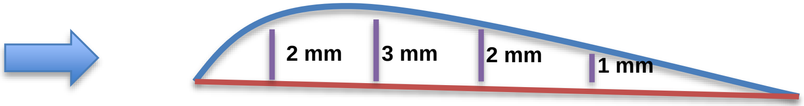
Challenges	State-of-the-art Limitations	Objectives
I. High resolution point cloud data	I. Not scalable to point cloud data	I. Object shape error estimation
II. Deformable parts	II. Statistical linear models	II. Non-linear model
III. Fault multiplicity for Six Sigma	III. Consider single fault or orthogonal multiple faults	III. Model with high discriminative ability
IV. Costly corrective actions	IV. No uncertainty quantification	IV. Uncertainty quantification
V. No samples at design stages	V. Use limited sensor data	V. Data augmentation using CAE Simulations

Object Shape Error Estimation

Example



Schematic Part



Example of cross section with shape error

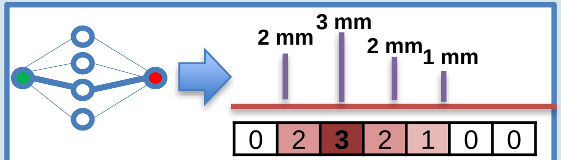
Current Approaches for
Root Cause Analysis
(statistical approaches)

$$\begin{bmatrix} & \cdots & \\ \vdots & \ddots & \vdots \\ & \cdots & \end{bmatrix} \times [2 \quad 3 \quad 2 \quad 1]$$

$\boldsymbol{f(x)}$ ***Shape Error***

$y\ (Root\ Cause)$

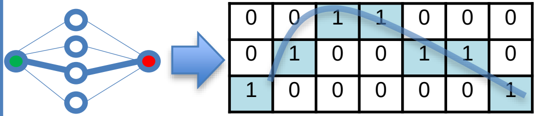
Proposed
Object Shape Error Estimation
(deep learning approach)



$\boldsymbol{f(x)}$ ***Shape Error***

$y\ (Root\ Cause)$

Current approaches for
Object Detection Methods
(VoxNet)



$\boldsymbol{f(x)}$ ***Shape Error***

$Object\ Classification$

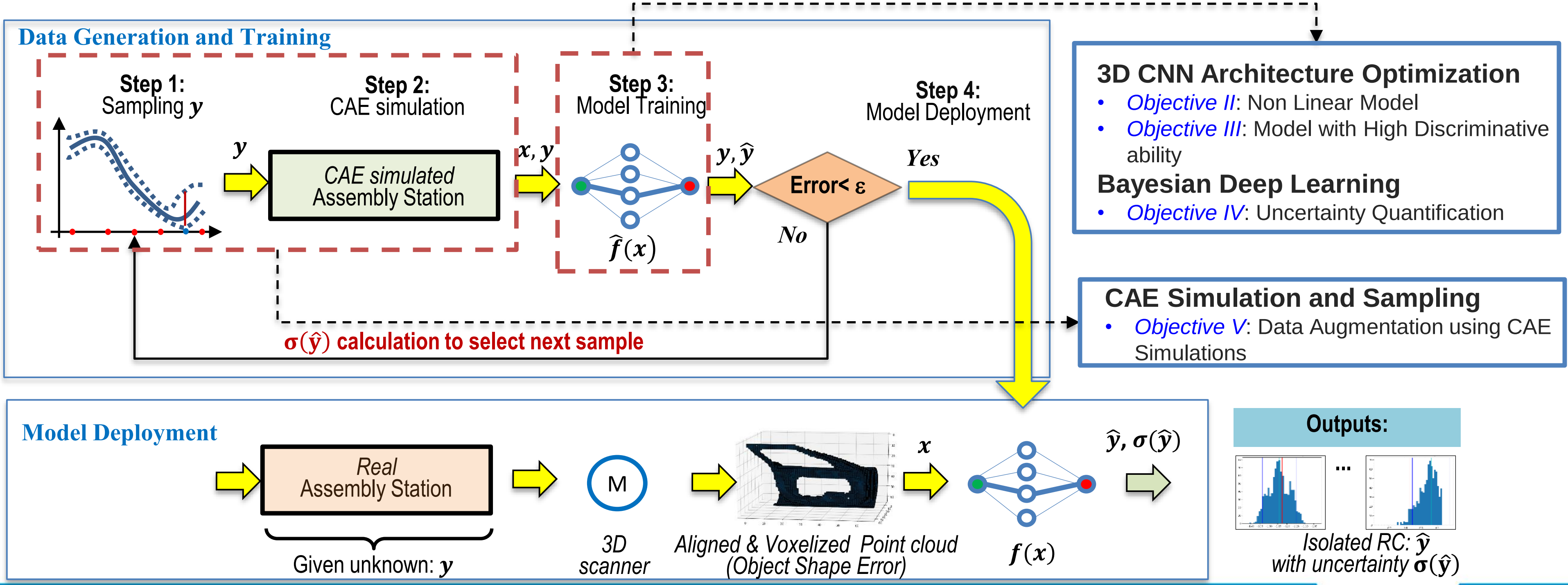
Limitations
- No scalable to point cloud data
- Single Fault / orthogonal m-faults
- Statistical linear models

Addressed in this paper
- High resolution point cloud data
- Fault Multiplicity for 6-sigma
- No samples at design stages

Limitations
- Only object detection
- Binary or RGB features

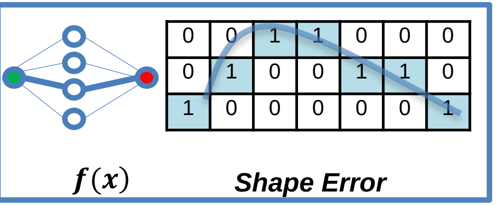
Methodology

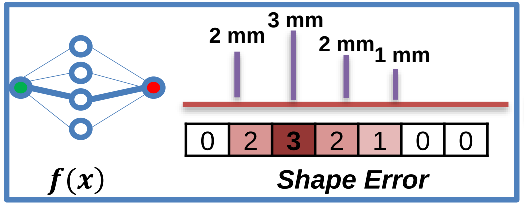
Object Shape Error Response (OSER) is based on
Bayesian 3D Convolutional Neural Networks (CNN) and Computer Aided Engineering (CAE) Simulations

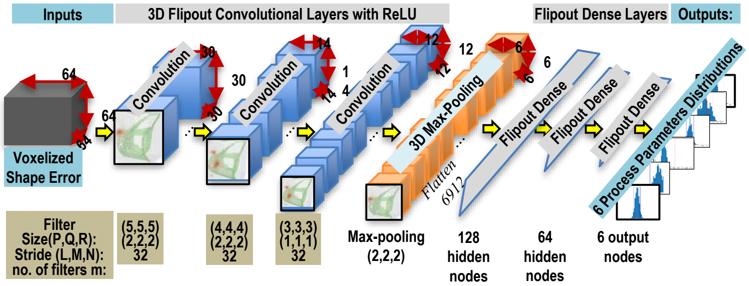


3D CNN Architecture Optimization

Current Object Detection Methods (VoxNet)	Proposed Object Shape Error Estimation	Rationale
Single channel input $32 \times 32 \times 32$	Multi-channel input $64 \times 64 \times 64 \times 3$	Increased granularity and shape error
Categorical outputs	Continuous outputs	Root Causes as *six-sigma level of variation*
Two 3D conv, one dense layer	Three 3D conv, three dense layers	Deformable parts, ill-conditioned systems, fault multiplicity
Deterministic Layers	Bayesian Flipout Layers	Uncertainty quantification to drive *costly corrective actions*







Bayesian Deep Learning

- **Bayesian deep learning enables uncertainty quantification hence integrating confidence in costly corrective decisions –**
- **Such cases of 3D CNN integration with Variational Inference Based Bayesian Deep Learning are limited**

Challenge

Model convergence given 2 million trainable parameters in the 3D CNN

Proposed Training* changes to ensure convergence

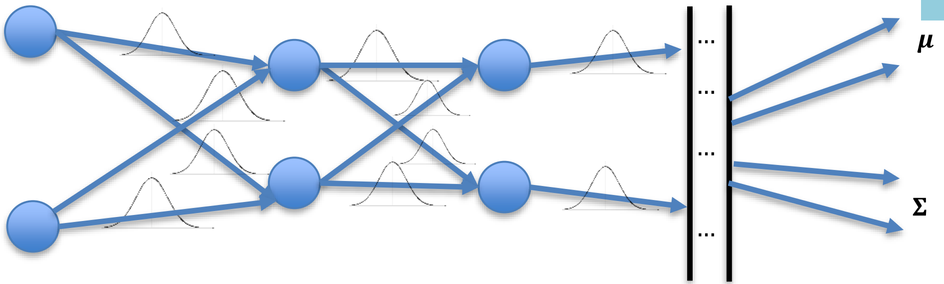
- Group normalization to account for small batch size
- Learning rate annealing for *kullback leibler Divergence Loss*

$\boldsymbol{w_{ij}} = \boldsymbol{N(\mu_{ij}, \sigma_{ij})}$

Uncertainty due to insufficient data

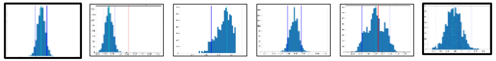
Estimated by assuming each weight in the network follows a normal distribution

Epistemic Uncertainty
(Unknown Unknowns)



Bayes-By-Backprop & Flipout Estimator

6 Process Parameters Distributions



$\boldsymbol{y} \sim \mathcal{N}_h(\boldsymbol{\mu}, \boldsymbol{\Sigma})$

Uncertainty due to system noise

Estimated by assuming the output follows a multi-variate normal distribution

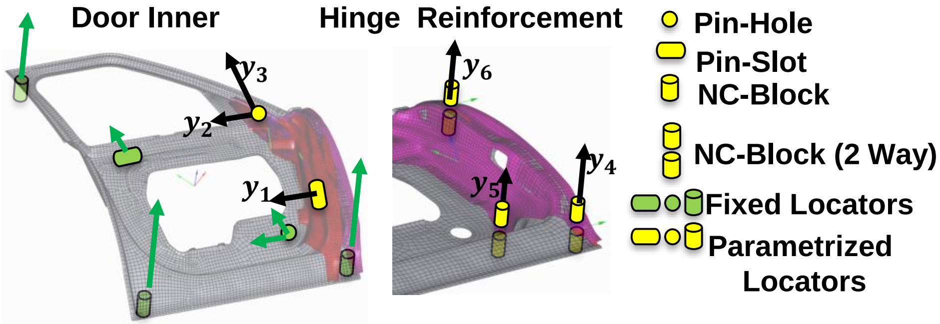
Aleatoric Uncertainty
(Known Unknowns)

Uncertainty $\sigma(\hat{y})$ = Epistemic + Aleatoric

**Two Nvidia Tesla v100 32 GB GPUs are used for model training*

Industrial Case Study: Assembly System Setup

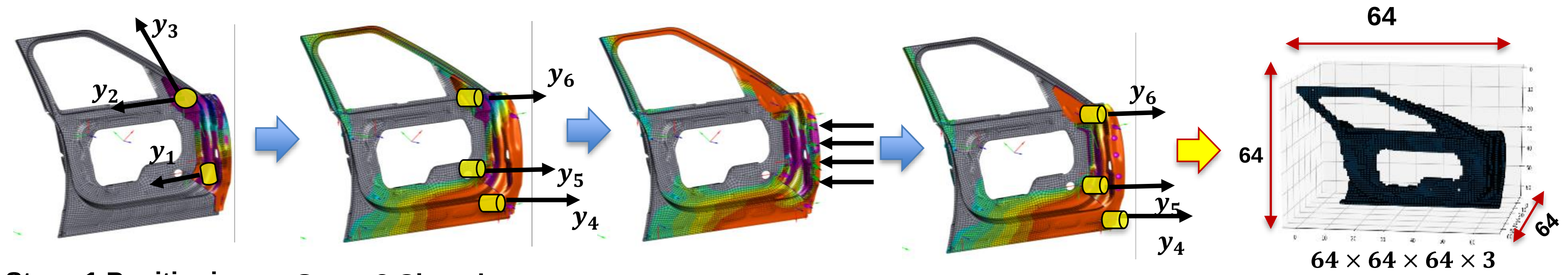
Multi-stage assembly process for automotive SUV door made of compliant parts



Six parametrized process parameters

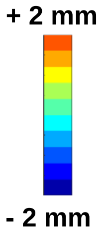
Challenges		Case Study Conditions
I.	High Resolution Point Cloud Data	10841 points
II.	Deformable Parts	Two compliant parts with part to part interactions
III.	Six Sigma Requirements	100% fault multiplicity, ill-conditioned
IV.	Costly Corrective Actions	Uncertainty quantification
V.	No samples at design stages	Use of CAE Simulations

Multi-Stage Assembly System



Stage 1 Positioning **Stage 2 Clamping** **Stage 3 Fastening*** **Stage 4 Release**

Voxelized Point Cloud Data x



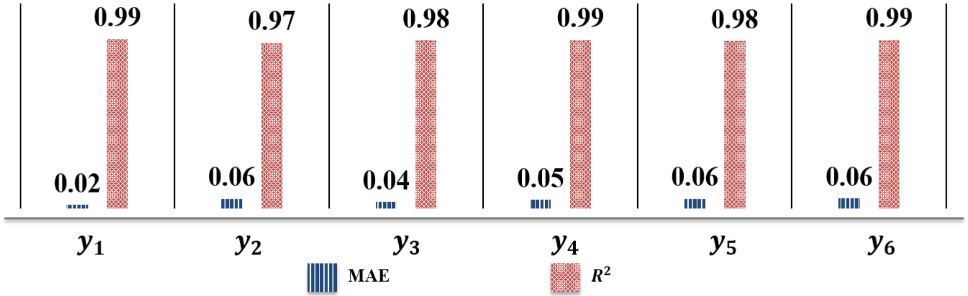
Process Parameter	Description	Unit	Training Range	Validation Range
y_1	Pin-slot displacement in x	mm	[-1,1]	[-2,2]
y_2	Pin-hole displacement in x	mm	[-1,1]	[-2,2]
y_3	Pin hole displacement in z	mm	[-1,1]	[-2,2]
y_4	Clamp 1 displacement in y	mm	[-2,2]	[-4,4]
y_5	Clamp 2 displacement in y	mm	[-2,2]	[-4,4]
y_6	Clamp 3 displacement in y	mm	[-2,2]	[-4,4]

**Self Piercing Riveting (SPR) is used as the fastening process*

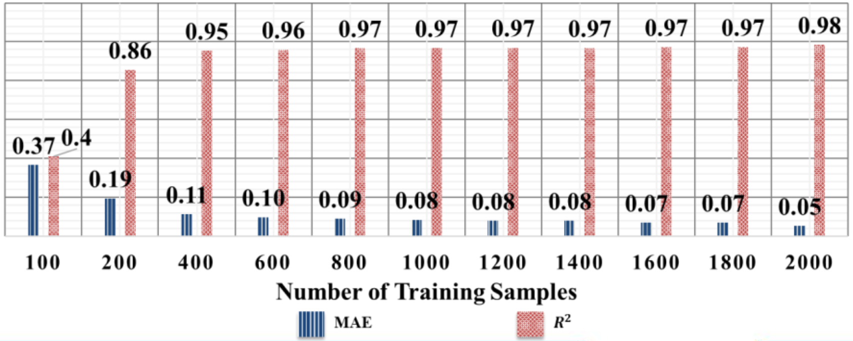
Results

- The threshold for Mean Absolute Error (MAE) is set at 0.05 mm as smaller variations cannot be detected by the 3D Optical Scanner
- $R^2 > 0.95$ verifies the non-linear and discriminable ability of the OSER methodology

Model performance across all process parameters:
MAE = 0.05 mm | R^2 = 0.98



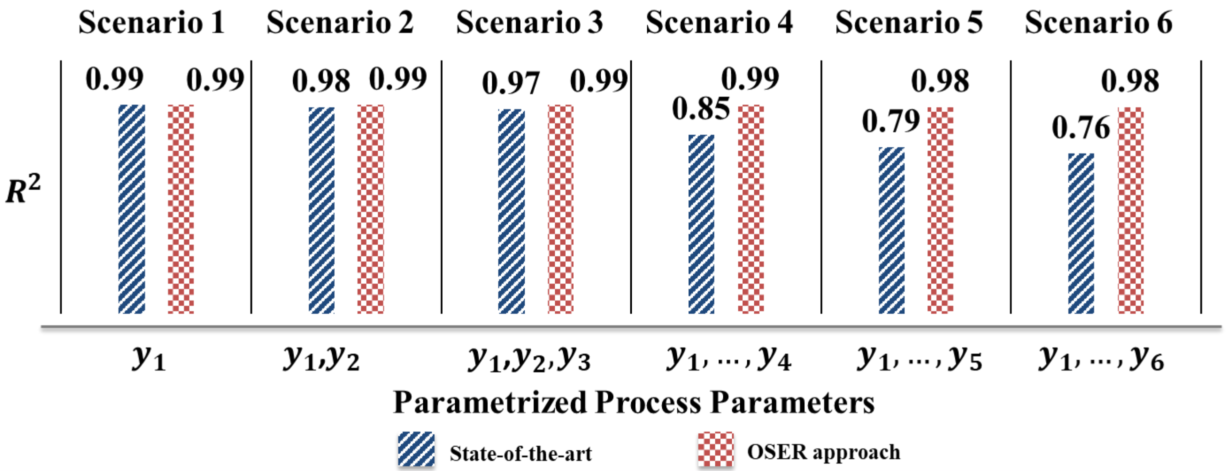
Model converges after training on **2000** samples
validation and testing is done on 500 samples



Benchmarking – Fault Multiplicity

Comparison with currently used approaches for Root Cause Analysis

On increasing fault multiplicity and including the effect of collinear process parameters i.e. parameters that give a very similar object shape error pattern, the performance of state-of-the-art statistical linear models decreases while OSER gives similar performance in all scenarios

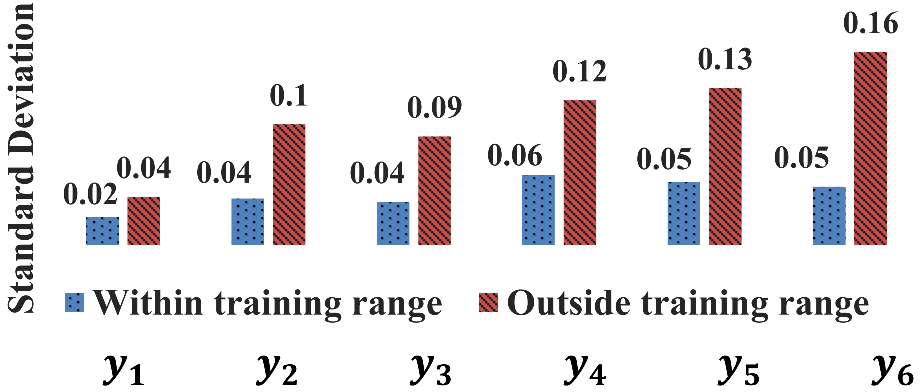


Benchmarking – Uncertainty Quantification

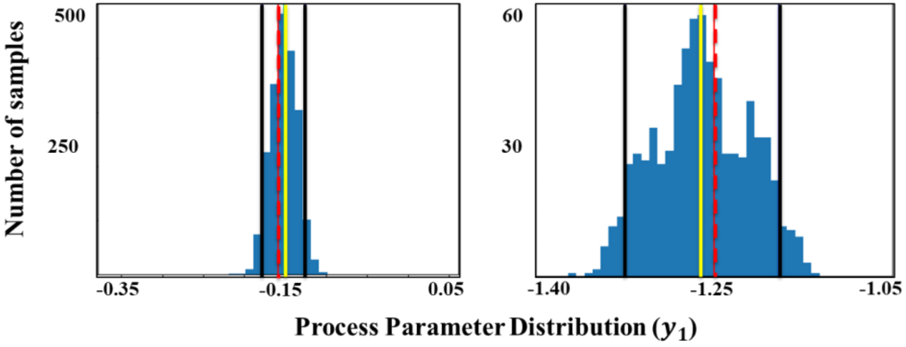
Currently used approaches for Root Cause Analysis do NOT quantify uncertainty

OSER enables uncertainty quantification hence integrating confidence in costly corrective decisions

Uncertainty* $\sigma(y)$ at 0.04 mm for within-training-range samples and at 0.11 mm for out-of-training-range samples



Histogram Plots for within-training and out-of-training ranges exhibit the increased uncertainty for unseen samples



**The uncertainty here is the Epistemic Uncertainty, the Aleatoric uncertainty is assumed to be constant (0.01 mm) given the level of noise in the system is constant*

Benchmarking – Machine Learning Models

Comparison with currently Not used machine learning models

- ❑ Upper limit on performance of current methods for RCA* is limited to 0.41 mm
- ❑ Other non-linear machine learning models give good performance but are unable to meet the required MAE threshold, quantify uncertainty and support other forms of learning

Models	Accuracy (MAE)		Goodness-of-fit (R^2)		Model Complexity (no. of trainable Parameters)	Training Time (minutes)	Uncertainty Estimates	Continual Learning	Transfer Learning
	Mean	SD	Mean	SD					
OSER (Bayesian 3D CNN)	**0.05**	0.03	**0.98**	0.01	1,997,286	424	**Yes**	**Yes**	**Yes**
OSER (3D CNN)	**0.05**	0.01	**0.98**	0.009	998,790	268	No	No	**Yes**
Gradient Boosted Trees	0.26	0.08	0.93	0.08	estimators: 300, depth 500	120	No	No	No
Artificial Neural Networks	0.28	0.09	0.91	0.07	2,809,222	358	No	No	No
Random Forests	0.29	0.09	0.92	0.08	estimators: 500, depth: 500	136	No	No	No
Support Vector Regression	0.38	0.09	0.85	0.1	32,524	180	No	No	No
Statistical Linear Models (Current Methods)	**0.41**	0.01	**0.76**	0.01	**32,524**	**10**	No	No	No

**The upper bound on Current methods for RCA that use statistical linear models is estimated using regularized linear regression*

Contributions & Applications

Contributions

Applications

Contributions	Applications
Object Detection to Object Shape Error Estimation I. Object Shape Error Processing	❑ RCA for other manufacturing processes (stamping, machining, additive manufacturing etc.)
3D CNN Architecture Optimization II. Non linear Model III. Model with high discriminative ability	❑ Automated RCA ❑ Zero Defect Manufacturing ❑ Reduction of Cost of Quality
Bayesian Learning Approach IV. Uncertainty Quantification	❑ Cost efficient optimal corrective actions ❑ Uncertainty based sampling
Integration with CAE simulations V. Data Augmentation using CAE Simulations	❑ Learning at early design stages ❑ Shorten New Product Introduction (NPI) lead time ❑ Right First Time & Continuous Improvement

Object Shape Error Response (OSER) using Bayesian 3D U-Net for Multi-Station Assembly Systems with Non-Ideal Compliant Parts

Predicting and Preventing Manufacturing Defects

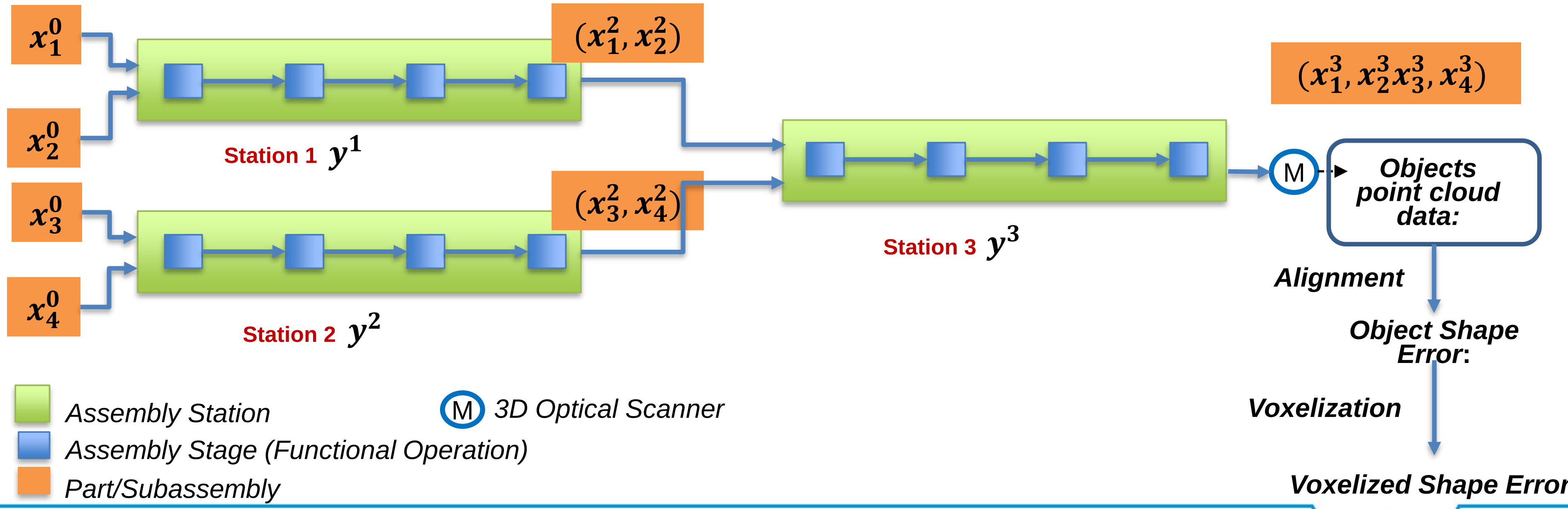
Presented by: Sumit Sinha
Sumit Sinha, Pasquale Franciosa, Dariusz Ceglarek

Digital Lifecycle Management (DLM)
WMG, University of Warwick, UK

WMG
THE UNIVERSITY OF WARWICK

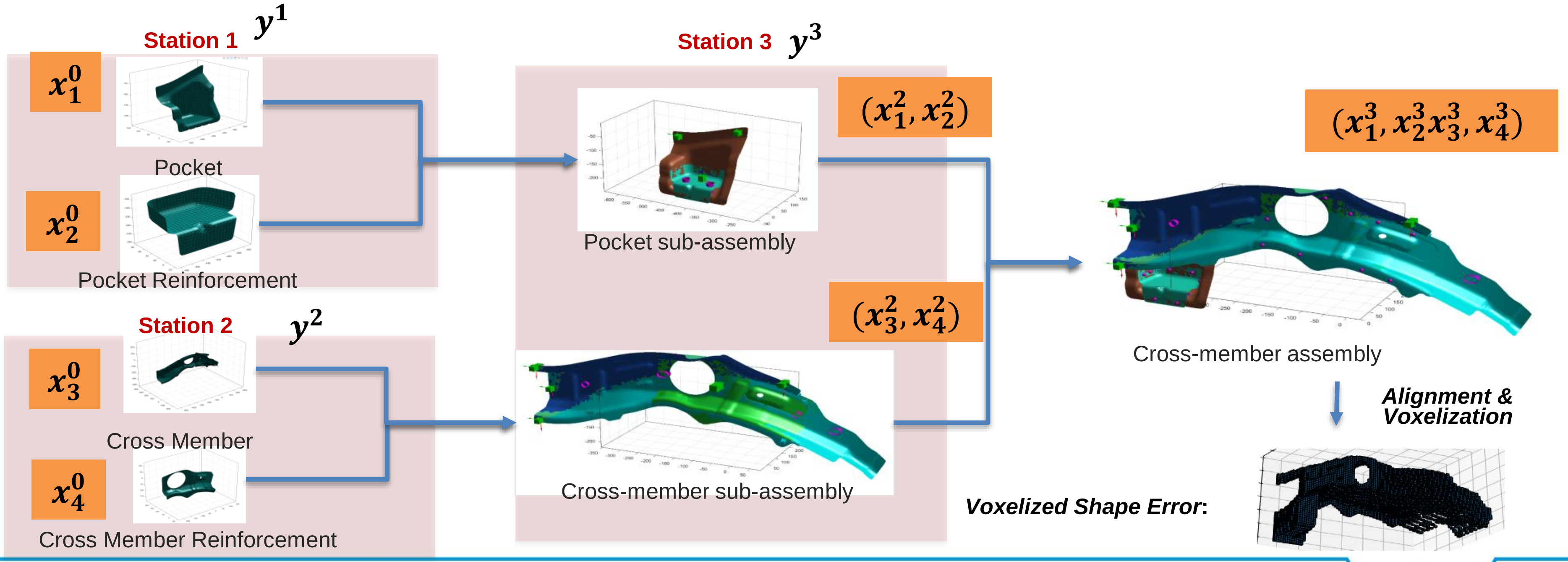
Multi-Station Assembly Systems

Multi-Station systems consist of **multiple stations** each having multiple number of stages



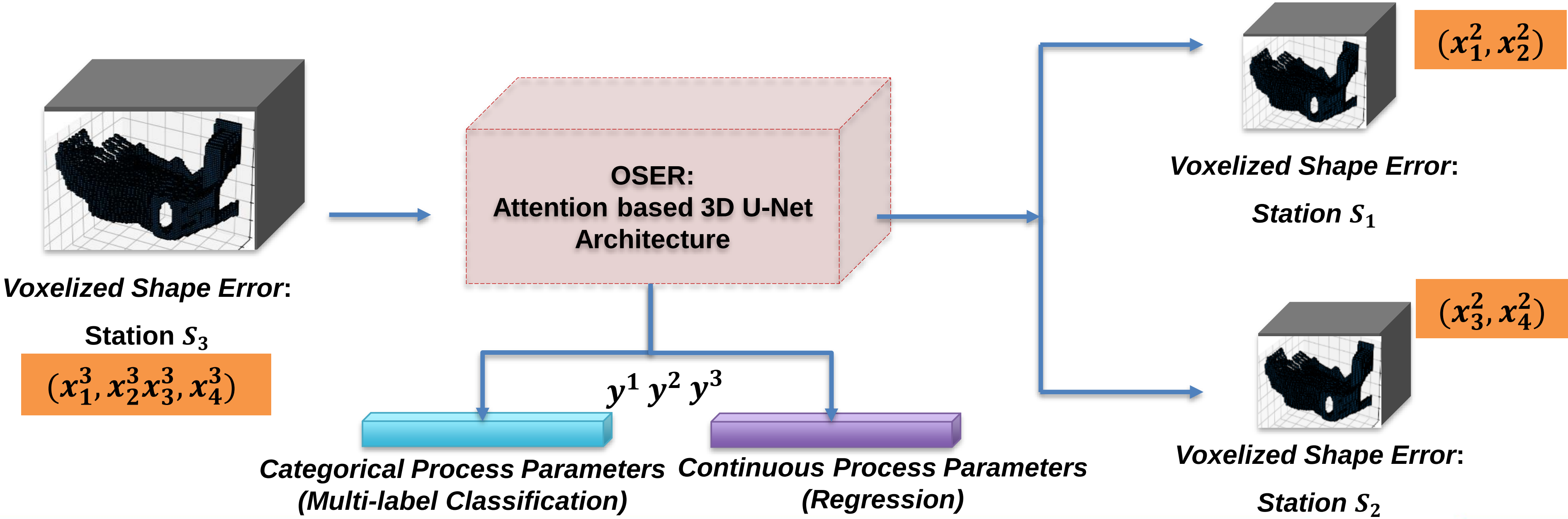
Case Study: Cross Member Assembly

4 part, 3 station cross-member assembly is used for verification and validation of the model



Methodology – Architecture Enhancement

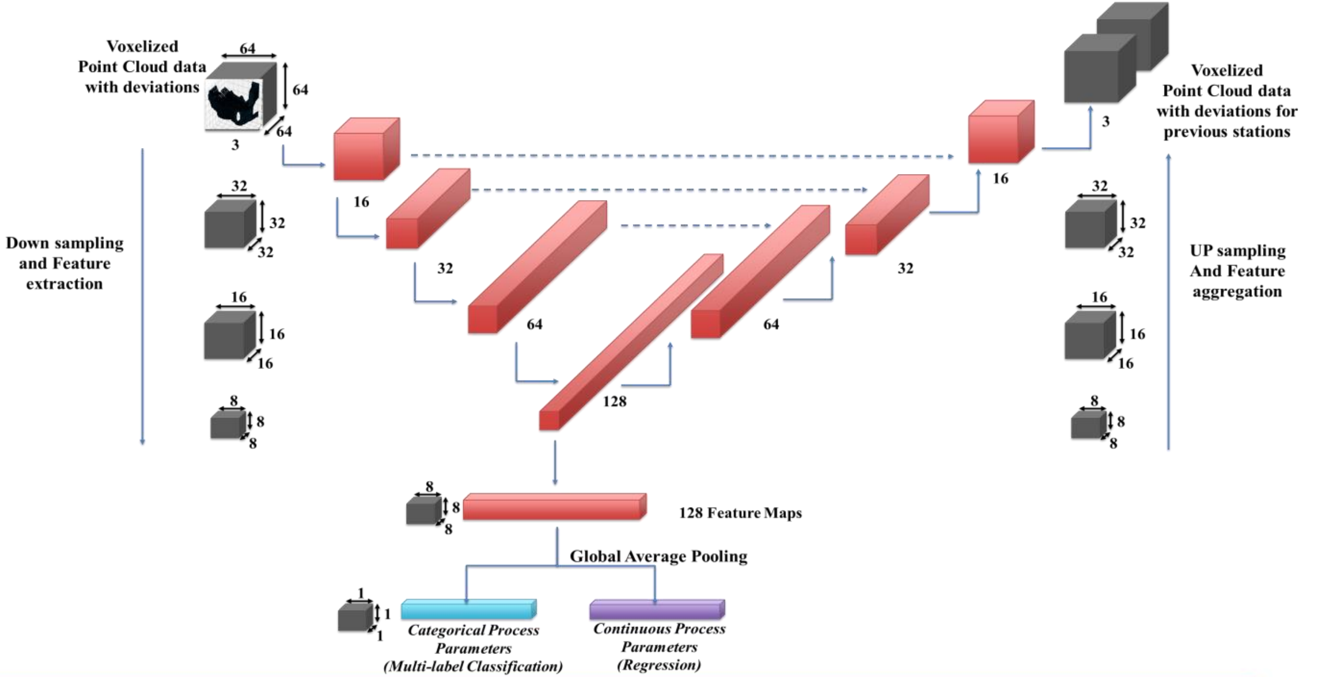
For multi-station systems process parameters and **object shape error** of previous stations need to be predicted



Process Parameters for all stations

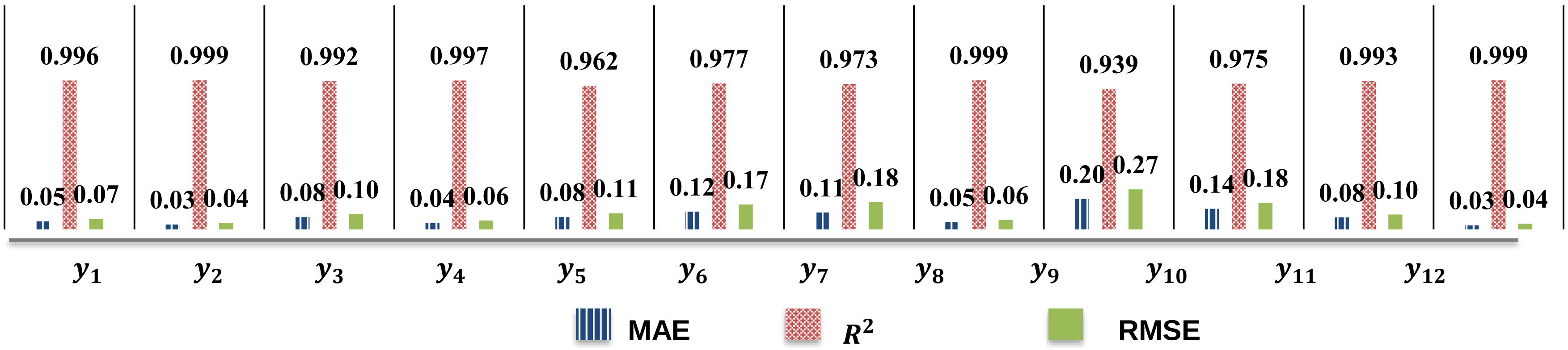
3D Architecture Selection & Optimization

The architecture is enhanced using a **3D U-Net Encoder Decoder** architecture with three output heads

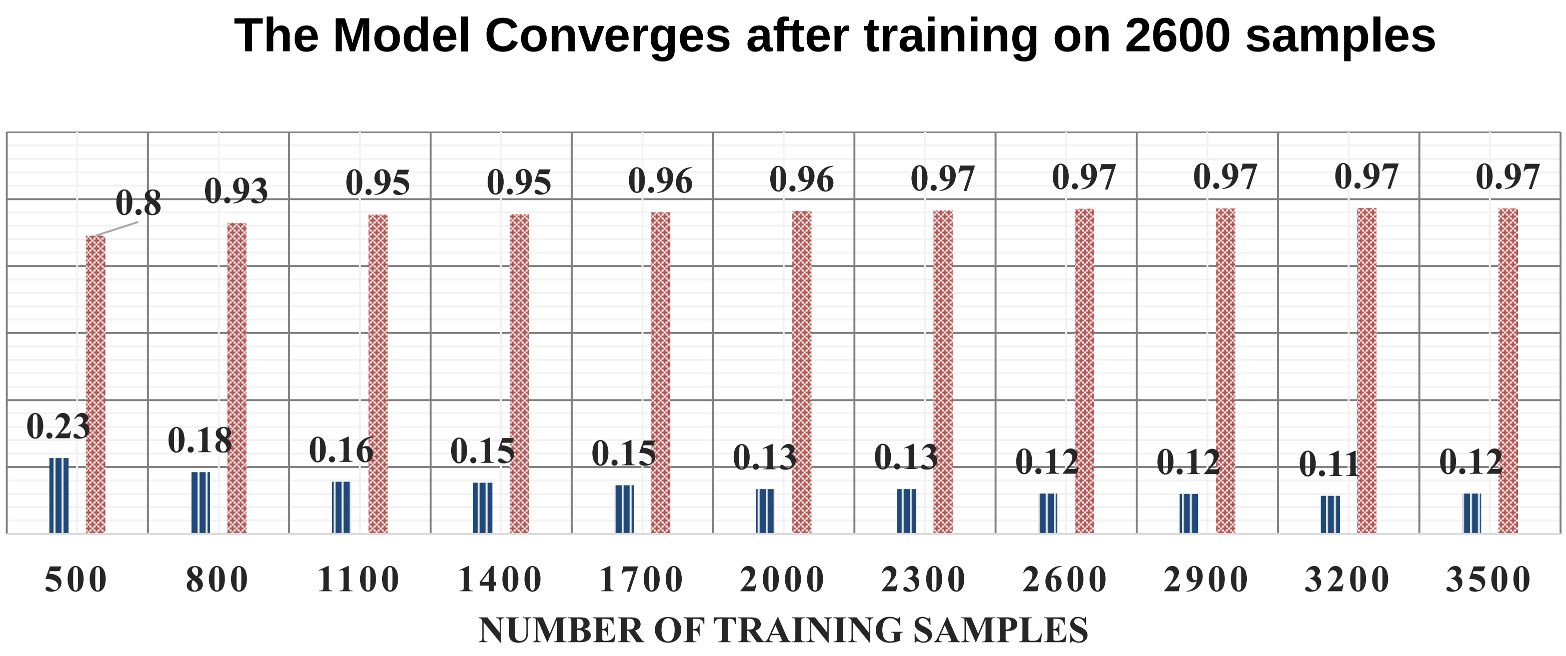


Results

The average MAE across all process parameters is 0.08 mm and the Average R^2 is 98% at 100% Fault Multiplicity



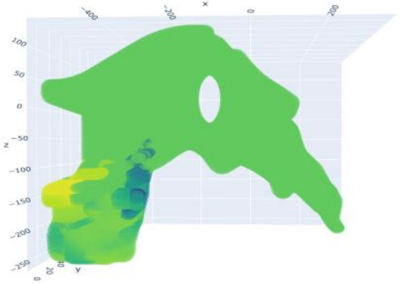
Results



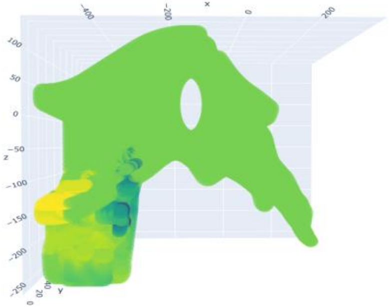
data_study_plot_test.html

Results

Object Shape Error Estimation accuracy for previous stages is at $RMSE = 0.0012$ and $R^2 = 0.96$



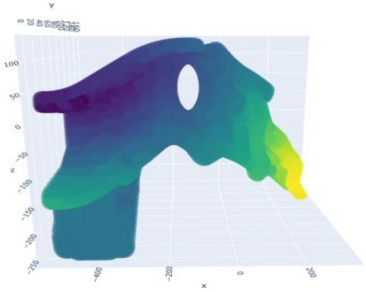
Actual



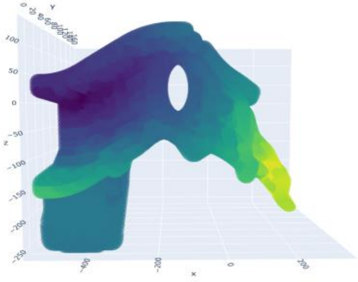
Predicted

Station S_1

MAE	**0.0002 mm**
RMSE	**0.002 mm**
R^2	**0.97**
R^2 **Adjusted**	**0.97**



Actual

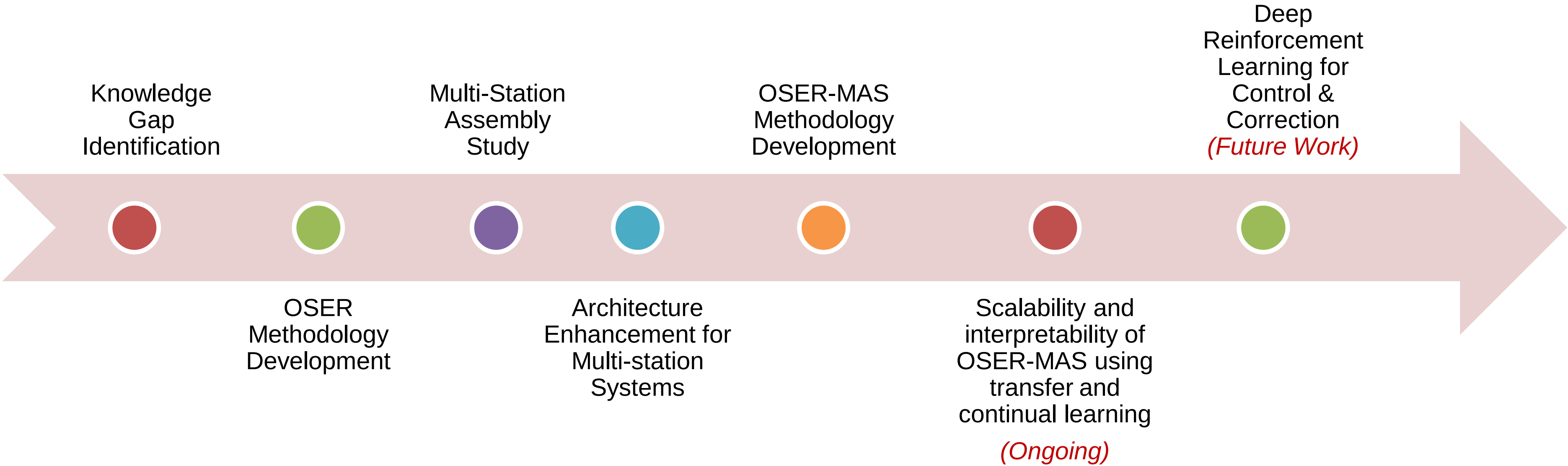


Predicted

Station S_2

MAE	**0.0012 mm**
RMSE	**0.014 mm**
R^2	**0.96**
R^2 **Adjusted**	**0.96**

Ongoing & Future Research



Object Shape Error Correction (OSEC) using Deep Reinforcement Learning for Multi-Station Assembly Systems

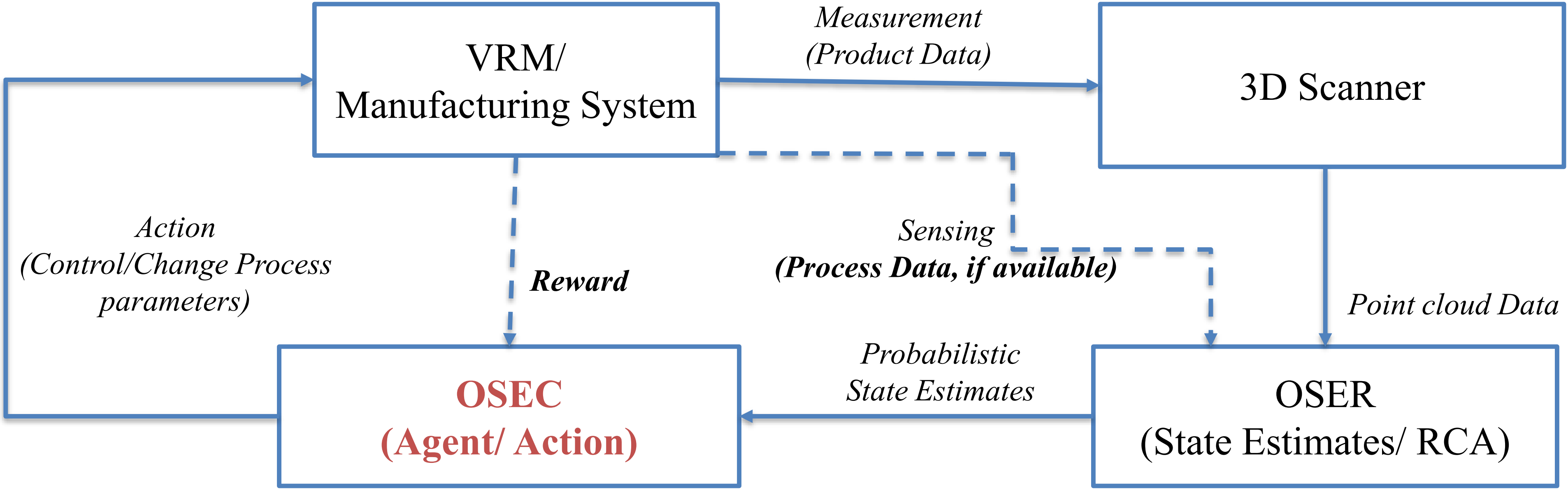
Predicting and Preventing Manufacturing Defects

Presented by: Sumit Sinha
Sumit Sinha, Pasquale Franciosa, Dariusz Ceglarek

Digital Lifecycle Management (DLM)
WMG, University of Warwick, UK

WMG
THE UNIVERSITY OF WARWICK

Problem Formulation



Objectives for control and Correction

System State that includes fault parameter estimates and upstream shape errors

Costs of change of each process parameter

Rigidity of the system (design, pre-production, full-production)

Cost of quality of each KPI

Objectives for control and Correction

Loss incurred due to KPIs not being at nominal

Loss incurred due to change in KCCs

$$Net\ Loss = \frac{1}{s*n}\sum_{p=1}^{s}\sum_{i=1}^{n}\boxed{K^i}(KPI^i_{Nominal} - KPI^{i,p}_{measured})^2 + \boxed{\lambda}\frac{1}{m}\sum_{j=1}^{m}\boxed{C^j}\left(KCC^j_{Current\ State} - KCC^j_{Next\ State}\right)^2$$

$K^i = KPI\ importance\ for\ ith\ KPI$

$C^j = Cost\ Coefficient\ for\ jth\ KCC$

User-defined system hyper parameters

$\lambda = System\ Rigidity$

Appendix

3D Convolutions

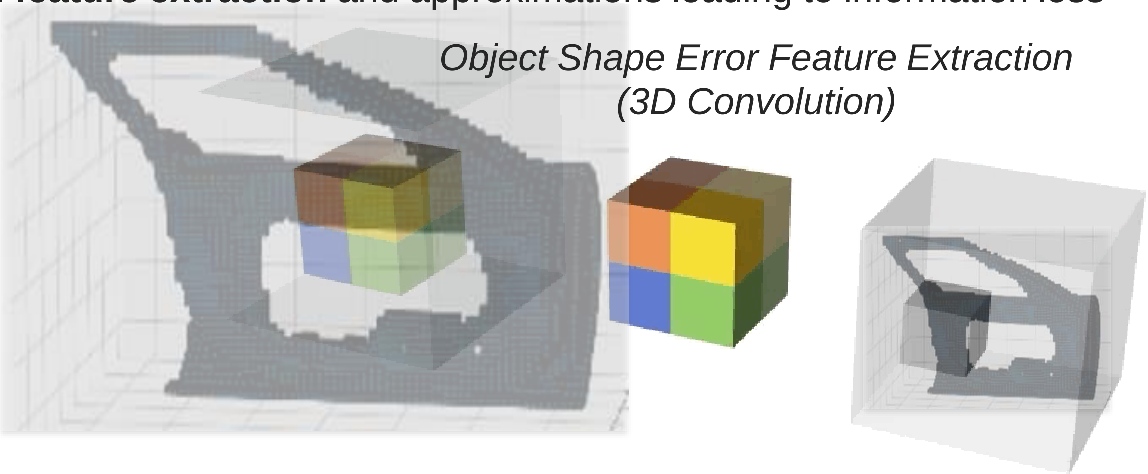
The Object Shape Error Feature extraction for compliant assemblies (Objects) is done using 3D Convolutions

Why?

- Account for location of the deviation (x, y, z) for 3D geometries
- Extract spatial and shape error $(\Delta x, \Delta y, \Delta z)$ features for all components of deviations
- Extract 3D geometric variation features while account for interactions between axes
- Eliminate the need for **manual feature extraction** and approximations leading to information loss

$\boldsymbol{x}: \{(x, y, z), (\Delta x, \Delta y, \Delta z)\} \rightarrow \{\boldsymbol{V}\}$

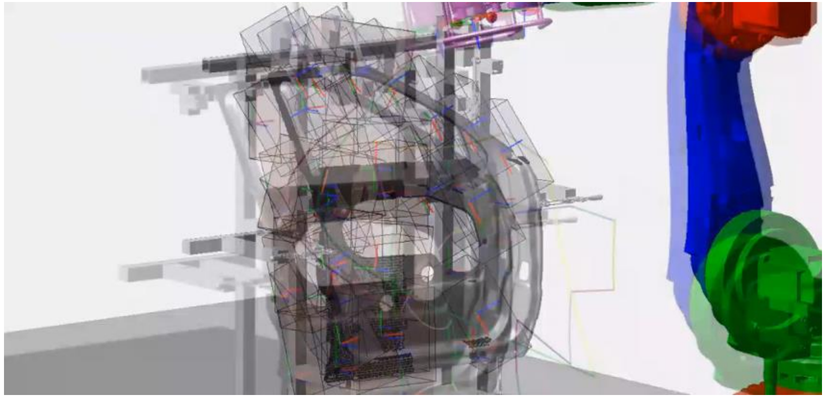
Object Shape Error Voxelization



Object Shape Error Feature Extraction (3D Convolution)

** The three components of deviation correspond to input channels characterising each voxel*
Approximations that convert to 2D/2.5D representations have been shown to give limited performance

Background – Data in Manufacturing



Data Source

- **Product Data**
  - *Points*
  - *Images*
  - *Point Clouds*
- **Process Data**
  - *Temperature*
  - *Force*

Data Resolution

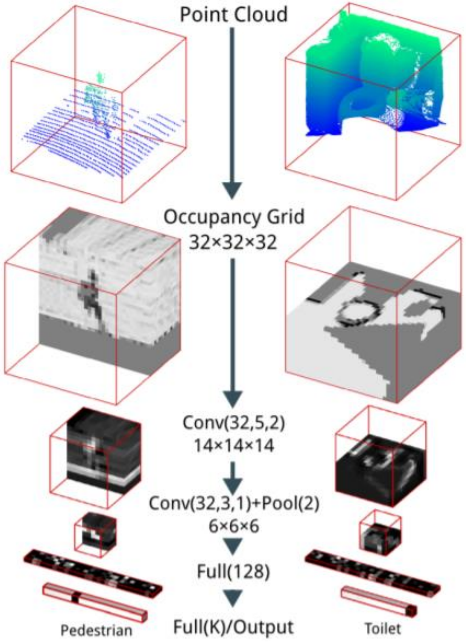
- **High Resolution**
  - 3D Point Cloud
  - Images
- **Low Resolution**
  - Points

Data Collection/Generation

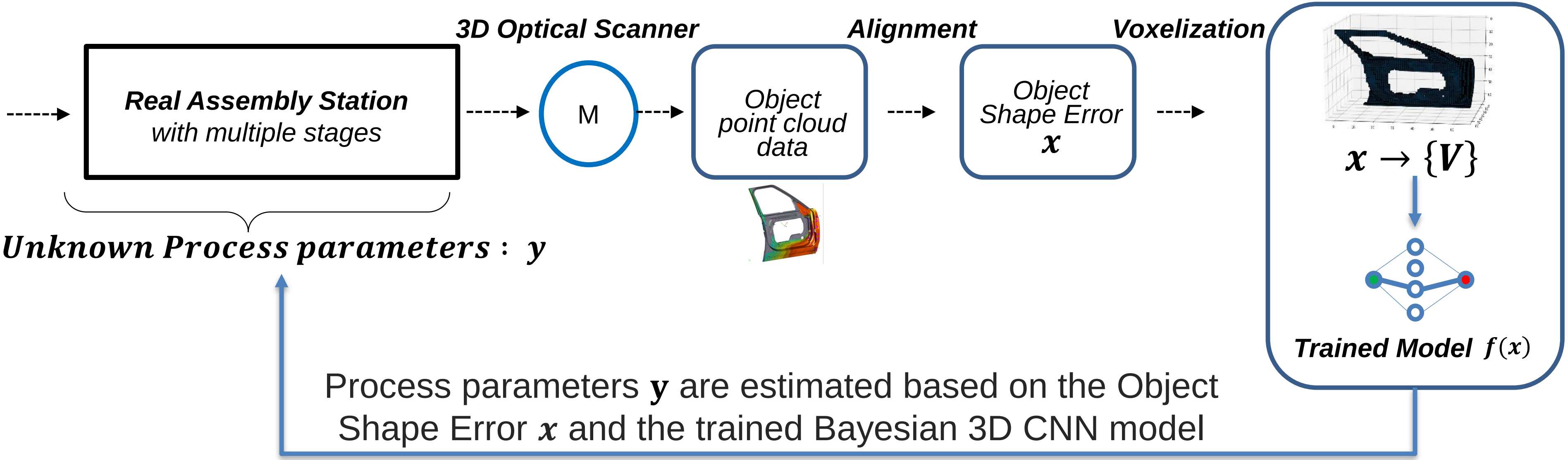
- **Physical System Data**
  - Measurement Systems (Scanners, CMM)
  - Process Sensors
- **Simulated Data**
  - Computer Aided Engineering Simulations

Goal: Automated Root Cause Analysis (RCA) of assembly system

VoxNet Architecture



Deployment



Process parameters $\mathbf{y}$ are estimated based on the Object Shape Error x and the trained Bayesian 3D CNN model

Root Causes are inferred as a subset of process parameters $\mathbf{y}$

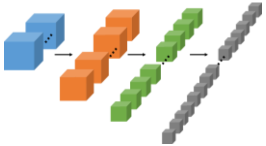
Methodology

Object Shape Error Response (OSER) has 4 steps and integrates Bayesian 3D Convolutional Neural Networks (CNN) & Computer Aided Engineering (CAE) Simulations

Step 1

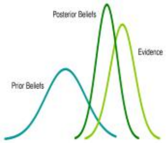
Object Shape Error Estimation

Step 2



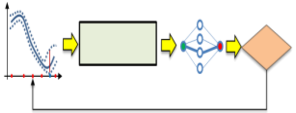
3D CNN Architecture Selection & Optimization

Step 3



Bayesian Deep Learning

Step 4



Model Training and Deployment

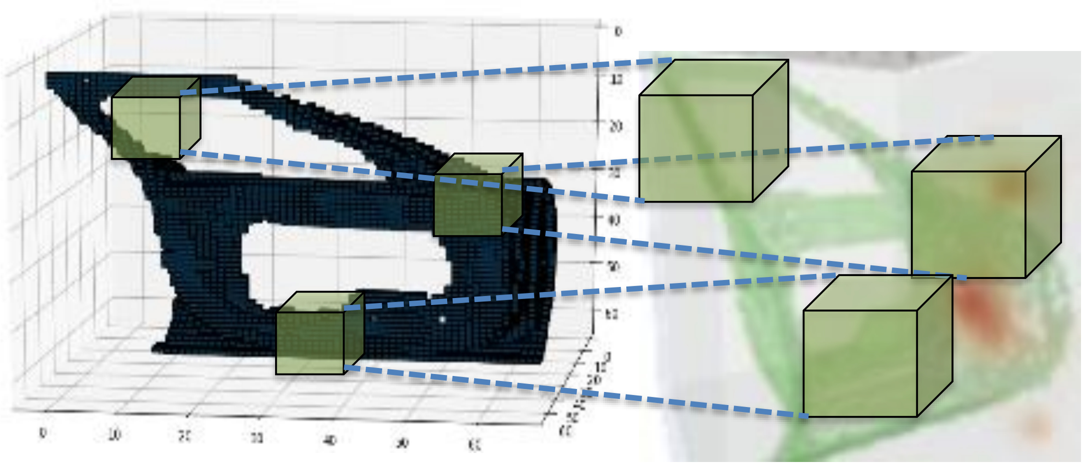
Mathematical Objectives

Step 1	Step 2	Step 3	Step 4
I. Object Shape Error Estimation	I. Non linear Model II. Model with high discriminative ability	III. Uncertainty Quantification	IV. Data Augmentation using Computer Aided Engineering Simulation (CAE)

3D Convolutions

The Object Shape Error Feature extraction for compliant assemblies (Objects) is done using 3D Convolutions

Such applications of **3D convolutions are limited*** due to the requirement of a large dataset for training



** Only two major 3D CNN architectures exist: VoxNet – 3D Object Detection, 3D U-Net – Tissue Scan Segmentation*