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Abstract—The paper proposes a novel Object Shape Error Response (OSER) approach to estimate the dimensional and geometric variation of assembled products and then, relate these to assembly process parameters, which can be interpreted as root causes (RC) of the object shape defects caused by the assembly system. The OSER approach leverages Bayesian 3D-Convolutional Neural Networks for RC isolation. Compared with the existing methods, the proposed approach (i) addresses a novel problem of applying deep learning for object shape error identification instead of nominal shape identification (object detection); and, (ii) overcome significant limitations in current approaches for Root Cause Analysis (RCA) of assembly systems which are frequently ill-conditioned (collinear fault patterns) with high fault-multiplicity (frequently encountered in 6-sigma strategy) while quantifying the prediction uncertainty. The verification of the proposed methodology is conducted based on the CAE model of a multi-stage assembly process for automotive SUV door made of compliant parts. The results demonstrate performance with R-Squared ($R^2$) = 0.98 and Mean Absolute Error (MAE) = 0.05 mm, thus improving RCA capabilities by 29% as compared to state-of-the-art methods.

Keywords—Bayesian Deep Learning, Manufacturing Assembly

I. INTRODUCTION

Object shape errors modelling and diagnosis are important enablers of Industry 4.0 and provide a transformative framework integrating facilitators such as big data, in-line 3D scanners, robotics and AI algorithms towards achieving near-zero-defect manufacturing. In this paper, the proposed 3D object shape error response (OSER) approach translates into estimating and discriminating between shape error patterns and linking them to manufacturing process parameters. Estimating at first and then reducing or eliminating these error patterns ensures dimensional product quality (as defined by GD&T) which is a major challenge for industries such as automotive, aerospace and shipbuilding. Two-thirds of the quality issues in the automotive and aerospace sectors are caused by dimensional variations [1]. The key goal is developing a root cause analysis (RCA) model that can identify the relationship between shape errors and manufacturing process parameters.

Past methods used to diagnose manufacturing dimensional quality faults are based on [2]: (i) statistical estimation; and, (ii) pattern matching based approaches. These approaches have been shown to have limitations in their applicability to complex, high dimensional and nonlinear systems [3] as these used linear models between process parameters and measurements of product dimensional quality [4][5][6][7]. This significantly limits the application of the methods for 3D object shape error modelling and diagnosis in manufacturing. The 3D shape error modelling and diagnosis used in manufacturing must have the capability to satisfy a number of requirements with respect to: (i) High data dimensionality of a batch of 3D objects which are defined by CAD (ideal parts) and point-clouds (non-ideal parts) with millions of points for each part or subassembly; (ii) Non-linearity due to compliant parts constrained by assembly fixtures and part-to-part interactions [8] [9]; (iii) Collinearity as many manufacturing systems are ill-conditioned [10] with error patterns of key process parameters being near parallel, thus, yielding widely discrepant results; (iv) High faults multiplicity as current near-zero-defects strategies require taking into consideration 6-sigma defects that lead to redefining defects from binary {$0,1$}, i.e., fault/no-fault, to continuous $<0,1>$, i.e., the fault being measured as a level of variation with dynamically changing threshold of acceptance, that significantly increases fault multiplicity; (v) Uncertainty quantification in the RCA output, as the identified RC frequently leads to costly corrective actions [11], it is crucial therefore to enhance the RCA model by an uncertainty estimation of the predictions; and, (vi) Dual data generation capability by using metrology gages and multi-physics-simulator needed for RCA model training. As the RCA model needs to be trained on a very large number of fault scenarios, which cannot be generated via real systems; and the training needs to be done before the real assembly systems are ready for production; there is a strong need to generate data via high fidelity multi-physics simulator. Then, the trained RCA model will use point-cloud data of real free-form surfaces obtained via robotic 3D scanner when implemented in a real system.

This paper will address the above requirements as follows: (1) Requirements (i)-(iv) by developing a 3D deep learning approach. This paper proposes a 3D Convolutional Neural Network (CNN) architecture that enables the extraction of spatial discriminative features from point clouds and hence, models non-linear relationships between features and process parameters. This approach has high performance for non-linear and ill-conditioned systems having high fault multiplicity; (2) Requirement (v) by leveraging Bayesian deep learning approaches that is enabled by Bayes-by-Backprop [12] and Flipout [13]. The proposed approach estimates each model parameter as a distribution (epistemic uncertainty) while also modelling the output estimates as parameters of a multi-variate distribution (aleatoric uncertainty); (3)
Requirement (vi) by making the developed 3D Bayesian deep learning compatible with point cloud data obtained via either metrology scanners or multi-physics simulator. The developed approach will utilize high fidelity multi-physics simulator of the assembly process, called Variation Response Method (VRM which was verified and validated for various assembly processes [14],[15]).

The key contributions of the paper are as follows:

1. Propose 3D OSER methodology based on a novel Bayesian 3D CNN architecture: it builds on the work done in the area of 3D Object Detection using point cloud data by expanding it to manufacturing systems where the key goal is not to detect the object but to estimate various shape error patterns present on the final object/product and relate these to process parameter variations within the system. To the best of our knowledge, this is the first paper to propose an uncertainty enabled model for RCA of assembly systems.

2. Propose a closed-loop framework for training and deployment of the Bayesian 3D CNN model that leverages a Computer-Aided Engineering (CAE) simulator known as VRM [14] to emulate the multi-stage assembly system. It behaves as a physics-based Digital Twin for generating augmented data that is close to the real system and can therefore, be used to train the model that can then be leveraged for applications such as RCA of assembly systems [16].

3. Implement, verify and validate this model on an assembly process for automotive SUV door made of compliant parts to estimate assembly process parameters from the output point-cloud data. Further benchmarking is done to highlight the model’s capabilities. Uncertainty estimation is done for different training and validation ranges.

The rest of the paper is organised as follows; Section II formulates the object shape error estimation problem, discusses the proposed Bayesian 3D CNN architecture and the overall steps required to train and deploy the model; Section III presents the industrial case study. Finally, conclusions and future work are summarized in Section IV.

II. METHODOLOGY

A. Object Shape Error Estimation in Manufacturing

Multi-stage assembly systems can be mathematically expressed as a state-space model where different states correspond to different stages of the manufacturing system [5]. The input is an object (set of parts to be assembled) entering the assembly process. Within the process, object shape errors can be introduced in any of the stages due to one or multiple variations in the process parameters and are further propagated through the stages (Fig. 1). Any object \( o \) at its design nominal shape is characterized by a set of nominal points \( P_o = \{p_{0k} \} \), \( k = 1, ..., n_o \), where \( p_{0k} \) is a vector consisting of the \( x \) and \( y \) coordinates of the \( k \)th input point and \( n_o \) represents the total number of points on object \( o \). The object here represents a single subassembly which is assembled in a single station, which can be understood as a collective reference to all parts used in this assembly station. \( d_{0k} = (d_{0k}) \) denotes the deviation of each point \( k \) after the nominal object \( o \) has gone through different stages of the process, where \( d_{0k} \) is a vector comprised of deviations of each point in \( x \) and \( y \) axes on object \( o \). An assumption made in this paper is that the assembly process has a single station which includes multiple stages \( s = 1, ..., 4 \) involving objects/parts: positioning (P), clamping (C), fastening (F) and release (R). Stage \( s = 0 \) is used to represent the incoming parts that include deviations from the previous processes such as part fabrication. As the object \( o \) goes through multiple stages the set of points are represented as \( P_{s0} \) while \( d_{s0} \) represents the deviations.

As the main goal of this paper is object shape error estimation, hence, the paper extends the problem formulation in object detection, which only considers the set of points \( \{p_{0k} \} [17] \), by including deviations for each point \( d_{0k} \) as additional features. This adds the required discriminative ability in the data hence, enabling object shape error estimation. Thus, the object shape error for object \( o \) after stage \( s \) can be represented as:

\[
x_s = \{x_{sk} \} = \{(p_{sk}, d_{sk})\}
\]

(1)

On the other hand, the set of all process parameters across all stages are denoted by \( y \) where \( y = \{y_1, ..., y_h \} \), \( h \) denotes the total number of process parameters. The deviation of points at each stage \( s \) for object \( o \) can be expressed as the sum of all deviations accumulated in all stages:

\[
d_s = \sum_{i=0}^{s} d_{i0}
\]

(2)

where \( d_{s0} \) represents the shape error of incoming object \( o \) caused by upstream manufacturing processes. At the end of the final assembly stage \( s = 4 \) the object shape error data for the assembly \( P^{s=4} \) is collected and decomposed into the nominal points \( P \) and their deviations \( d^{s=4} \) by using alignment techniques, where \( P^{s=4}, d^{s=4} \) are now a collective reference to the set of all incoming objects that have been assembled. The measurement system error \( \varepsilon \) is considered to be negligible (\( \varepsilon \approx 0 \)). The combined object with errors is represented as a point cloud of non-ideal parts where \( d_{s0} \) can be considered as features at each point \( p_{sk} \):

\[
x_s = \{x_{sk} \} = \{(p_{sk}, d_{sk})\}
\]

(3)

\[
\begin{align*}
P_{s0} & \stackrel{\text{Assembly Station with PCFR stages}}{\longrightarrow} P_{s0}^{d} \\
\text{Process parameters: } y & \text{ } \quad \text{PCFR: Position-Clamp-Fastening-Release} \\
\text{3D scanner} & \text{ } \quad \text{Objects point cloud data } P^f = \{p^f \} + \varepsilon
\end{align*}
\]

Fig. 1. Object Shape Error Propagation in Assembly Systems

The Bayesian 3D CNN model training aims to learn assembly process transfer function \( f(.) \) (equivalent to state transition matrix in [18]). The function \( f(.) \) is parameterized by weights and biases of a CNN that can accurately estimate the process parameters \( y \) given the point cloud data of non-ideal \( x^f \) parts collected from the system:

\[
y = f(x^f)
\]

(4)

The high accuracy of the 3D CNN in estimating all assembly process parameters \( y \) provides the underlined capability of the OSER approach for high root cause isolability. Essentially within assembly systems root causes (RC) are estimated as a subset of the process parameters.

B. Bayesian 3D CNN Model Architecture

Building on the work done on voxel-based approaches for 3D object detection such as VoxNet [17], the research proposes a Bayesian 3D CNN architecture to enable object shape error estimation. The 3D convolutions aggregate features from the input which are then utilized by the fully
connected layers and mapped to process parameters. The model consists of three 3D convolutional Flipout layers, a 3D max-pooling layer followed by three fully connected Flipout layers, the final layer estimates parameters of the predictive distribution for all process parameters. Given the Bayesian framework, each parameter of the Bayesian 3D CNN model follows a distribution. Each parameter is approximated using variational inference approach assuming that the posterior follows a normal distribution. The overall model has 1,997,286 trainable parameters. Output nodes have linear activation units. Fig. 2 shows the proposed Bayesian 3D CNN model architecture with annotated hyper-parameters.

C. Voxelization

In the presented OSER approach the simulation output represented as mesh or point cloud data \( \{(p_k, d_k^x)\} \) is transformed to voxel grids \( \{V_{u,v,w}\} \) with discrete voxel coordinates \((u,v,w)\) in the following way: for all points \( p_k = (x_k, y_k, z_k) \) that fall within a voxel grid \( \{V_{u,v,w}\} \) the maximum value of \( d_k = \max(x_k, y_k, z_k) \) characterizes the features of the corresponding voxel grid and is represented as \( \{V_{u,v,w,d}\} \). Then, the voxelization techniques VoxNet [17] used in object detection and segmentation. Note that in object detection approaches traditionally voxel grids are characterized by either binary voxels or voxels containing RGB values for each point.

D. Model Training and Deployment

Training of the model is done in a closed-loop framework using data generated by VRM. The key steps of the proposed framework are summarized below (Fig. 3):

Step 1 – Sampling: Process parameters \( y \) are sampled from the allowable ranges. Latin Hypercube Sampling [19] is used to generate initial process parameter sample values given it distributes samples optimally across the \( h \) – dimensional process parameter space by stratifying the sample set. The consecutive samples are generated using Monte Carlo/NT-net [20] sampling based on the model uncertainty \( \sigma(y) \).

Step 2 – Response Evaluation using VRM Simulation: The samples are used as input to the VRM to simulate the assembly process and generate the output mesh from which the point cloud and deviations of each point are extracted after the desired stage \( s \) of the assembly system \( x^s = \{(p_k, d_k^x)\} \).

Step 3 – Model Training: The point cloud and deviation data of object shape errors along with the respective process parameters \( x^s = \{(p_k, d_k^x)\}, y \) are used for model training. Note that \( x^s \) is voxelized \( \{V_{u,v,w,d}\} \) before it is used for training. The loss function optimized while training comprises the sum of Kullback-Leibler (KL) divergence for each layer and the negative log-likelihood of the predictive distribution. The predictive distribution is modelled as a multivariate normal \( \mathcal{N}\) with \( h \) components (same number of components as the number of process parameters \( h \)). The predictive distribution is assumed to have a diagonal covariance matrix \( \Sigma \). The scale parameters in the diagonal are assumed to be fixed since the noise has been assumed to be negligible. Adam method for stochastic optimization with default parameters was used to optimize the loss function while training [21]. After each iteration of training the model is evaluated on the validation set. For evaluation, Monte Carlo (MC) sampling from the model is done and the sample means \( \bar{y} \) and standard deviations \( \sigma(y) \) are estimated for each process parameter. \( \sigma(y) \) represents the epistemic uncertainty while the fixed scale parameters of the predictive distribution represent the known aleatoric uncertainty [22]. Given the assumption of negligible measurement noise, aleatoric uncertainty is considered to be negligible and hence, the overall uncertainty in the prediction can be assumed to be equal to epistemic uncertainty \( \sigma(y) \). This uncertainty is used for sampling in the next iteration. Mean Absolute Error (MAE) between the model estimates \( \bar{y} \) and actual value \( y \) across all process parameters \( h \) is used as the metric for model performance evaluation given the ease of interpretation and given that the model outputs are continuous and real-valued. Training is stopped when MAE is below the required threshold \( \epsilon \). The threshold value for this metric is determined based on the quality requirements for a specific product as required by design tolerances and the accuracy of the measurement system. The model is trained within the measurement system accuracy. For example, automotive body assembly process tolerances are within \([-1 \; \text{mm}, 1 \; \text{mm}\] and the 3D optical scanner used has a repeatability of 0.05 mm.

Step 4 – Model Deployment: After training the model can be deployed within an actual system. The data collected from the 3D scanner \( P^x \) is aligned to obtain point cloud and deviations \( x^s = \{(p_k, d_k^x)\} \) and then, voxelized \( V_{u,v,w,d} \) before it can be given to the trained model for conducting RCA inference. Inferencing estimates the process parameters for a given \( x^s \) (3) using MC sampling from the trained model. Using these samples, process parameters (distribution mean) \( \bar{y} \) and their uncertainty (distribution standard deviation) \( \sigma(y) \) can be estimated. The sample mean \( \bar{y} \) is considered as the model estimate \( \bar{y} \) while \( \sigma(y) \) quantifies the uncertainty. Further, the RCs can be inferred as a subset of \( \bar{y} \). The work has been implemented using Python 3.7 and TensorFlow - GPU 2.0 [23] and TensorFlow Probability 0.8. A python library named Deep Learning for Manufacturing (DLMFG) has been developed to train, validate and replicate results of the proposed OSER methodology. For this paper, both, the data generation and evaluation of the OSER methodology have been done using VRM. The Nvidia Tesla V100 32 GB is used for model training and deployment.

![Fig. 2. Bayesian 3D CNN Model Architecture](image2)

![Fig. 3. Model Training and Deployment Framework](image3)
III. CASE STUDY

For verification and validation of the proposed OSER approach, an automotive assembly of two components namely, the door inner and hinge reinforcement are selected. The assembly setup and parameters are shown in Fig. 4. The assembly process is controlled by the six \( (h = 6) \) parametrized process parameters \( y_1, y_2, ..., y_6 \) (depicted using yellow symbols in Fig. 4). Assembly parameters such as pin-hole, pin-slot and NC blocks for the door inner are considered constant (depicted using green symbols in Fig. 4) hence are not paramaterized. Data is collected after stage \( s = 4 \). The point cloud is characterized by \( n = 10841 \) points, which are pre-processed and voxelized to \( (u, v, w) = (64, 64, 64 \) voxel grids. The deviation features \( d \) include deviations in all directions for all points \( (x_k, y_k, z_k) \). The assembly consists of four stages (Fig. 5): Stage 1 involves positioning (i) the door inner on the pin-hole, pin-slot and the three NC blocks (not parametrized; marked in green in Fig. 1), (ii) hinge reinforcement using the pin-slot \( (y_1) \), pin-hole \( (y_2, y_3) \); Stage 2 comprises of clamping two parts together using three NC-Blocks with clamps \( (y_4, y_5, y_6) \); Stage 3 involves fastening/joining of the two parts using self-piercing riveting (SPR); and, finally, Stage 4 involves releasing the clamps \( (y_4, y_5, y_6) \) after the fastening is completed. The training range for all process parameters is \([-1 \text{ mm}, 1 \text{ mm}]\) while the validation range is \([-2 \text{ mm}, 2 \text{ mm}]\). Point cloud and deviation data \( (p_k, d_k) \) are collected after release, i.e., Stage 4 (Fig. 5). The data is voxelized \( V = \{ 64, 64, 64 \} \) and used as model input and the process parameters \( y_1, y_2, ..., y_6 \) are used as model outputs.

\[ \text{MAE} \] across all process parameters is below the threshold which is selected to be 0.05 mm for automotive assembly applications as the impact of variations less than 0.05 mm is not detectable by the 3D surface scanner. After this, the model is ready for deployment with data collected from 3D optical scanners. Real data collection is done using WLS400A [25] mounted on an ABB robot.

In summary, the industrial assembly process selected for case study consists of (i) high dimensionality point cloud (10841 points); (ii) non-linearity as induced by fixturing (N-2-1, where \( N=6 \)), two compliant parts (door inner and hinge reinforcement) and part-to-part interactions (door inner to hinge reinforcement); (iii) collinearity induced by fixturing as locators: \( y_4, y_5, \) and \( y_6 \) are within 5 degrees of collinearity (-3 to 2-degree deviation from axis y); and, (iv) high fault multiplicity as we take into consideration 6-sigma defects at the level of variation within 3D scanner accuracy (\(<0.05\text{mm}\)) that significantly increases fault multiplicity from zero to 6 process parameters manifesting errors (100% fault multiplicity). The door assembly requirements are: (1) Product: Design tolerances of door assembly: \(<1.0, 1.0\> \text{ mm}, \) (2) Process: Fixturing calibration and commissioning is achieved within \(<0.1, 0.1\> \text{ mm}, \) and (3) Shape error detection: Using the 3D optical scanner for measurement.

Key Performance Indicators (KPIs) used for assessment of the results are as follows: (i) Mean Absolute Error (MAE) \(<0.05\) and, (ii) \( R^2>0.95 \) for the model to have the capability to explain more than 95% variance in the process parameters under the assembly system Requirements (ii)-(iv).

A. Results

The KPIs used for quantification of model performance and are summarized for all \( y_1, ..., y_6 \) in Fig 6. The model converges with average MAE across all process parameters equal to 0.05 (below the required threshold) and average \( R^2 \) equal to 0.98 after training on 2000 samples. For validation purposes, this study trained both Bayesian 3D CNN and a standard version of the model, i.e., 3D CNN with the same architecture as in Fig. 2 but without Bayesian layers. Both models have similar performance as shown in Table I.

![Fig. 4. Assembly Process Parameters](image)

![Fig. 5. PCFR Stages of the Assembly Process](image)

![Fig. 6. MAE and \( R^2 \) across all process parameters](image)

B. Benchmarking and Discussion

The benchmarking analysis is conducted by using the six requirements as listed in Section I. The case study and results along with analysis of collinearity, multiplicity and uncertainty are used to demonstrate the capabilities of the proposed approach to fulfill the aforementioned requirements.

The benchmarking analysis of the proposed 3D OSER approach with the state-of-the-art is discussed on two levels:

1. OSER vs. currently used approaches at production phase when point cloud data is available – The benchmarking is conducted on two levels: (a) RCA; and, (b) RCA with uncertainty quantification; and with underlined six requirements:
TABLE I. RESULTS

<table>
<thead>
<tr>
<th>Models</th>
<th>Accuracy (MAE)</th>
<th>Goodness-of-fit ($R^2$)</th>
<th>Model Complexity (no. of trainable Parameters)</th>
<th>Training Time (minutes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OSER (Bayesian 3D CNN)</td>
<td>0.05</td>
<td>0.03</td>
<td>0.98</td>
<td>0.01</td>
</tr>
<tr>
<td>OSER (3D CNN)</td>
<td>0.05</td>
<td>0.01</td>
<td>0.98</td>
<td>0.009</td>
</tr>
<tr>
<td>Gradient Boosted Trees</td>
<td>0.26</td>
<td>0.08</td>
<td>0.93</td>
<td>0.08</td>
</tr>
<tr>
<td>Artificial Neural Networks</td>
<td>0.28</td>
<td>0.09</td>
<td>0.91</td>
<td>0.07</td>
</tr>
<tr>
<td>Random Forests</td>
<td>0.29</td>
<td>0.09</td>
<td>0.92</td>
<td>0.08</td>
</tr>
<tr>
<td>Support Vector Regression</td>
<td>0.38</td>
<td>0.09</td>
<td>0.85</td>
<td>0.1</td>
</tr>
<tr>
<td>Regularized Linear Regression</td>
<td>0.41</td>
<td>0.01</td>
<td>0.76</td>
<td>0.01</td>
</tr>
</tbody>
</table>

RCA: as discussed in Section 1, the state-of-the-art models used for assembly process RCA such as [26][27] are linear and can be classified as regularized linear regression approaches (Table I). Hence, their upper limit performance can be estimated by using regularized linear regression on all point deviations $d$ within the point cloud. They also use a limited number of sampled points from the point cloud on a single part (less than 100 out of $>10,000$) which additionally limit their performance for assembly processes. The OSER methodology validation against the six requirements as presented in Section I as follows. Requirement (i) is fulfilled by the proposed voxelization approach which ensures that irrespective of the dimensionality of the point cloud, it is transformed into a sparse tensor of dimensions $(64, 64, 64, 3)$ which preserves information in terms of the object spatial structure and point deviation features. This also enables the application of the OSER based models that require a regular data structure as input. State-of-art-approaches would need additional dimensionality reduction as the point cloud dimensionality increases. Secondly, the model performance of the state-of-the-art regularized linear regression approaches is at $MAE = 0.41$ and $R^2 = 0.76$, which is unsatisfactory as compared to the required $MAE<0.05$, $R^2>0.95$. This is due to the fact that the regularized linear regression model can explain only the linear variance in the system. By comparison, the proposed OSER model demonstrates good performance at $MAE = 0.05$, $R^2 = 0.97$, hence fulfilling Requirements (ii), (iii) and (iv). Fig. 7 compares the performance of regularized linear regression (upper limit on state-of-the-art) with the proposed OSER approach under different levels of fault multiplicity and collinearity. For example, in scenarios 1, 2 and 3 (fault multiplicity up to 50%) both approaches have similar performance. However, in scenarios 4, 5 and 6 as the fault multiplicity increases and parameters 4, 5, and 6 are simultaneously at fault, and with simultaneously induced collinearity between process parameters and input, the performance of linear model decreases while OSER performs above the required threshold ($R^2 >0.95$).

To comprehensively assess the OSER against existing machine learning techniques involving multi-output regression [28] though not currently used for RCA of assembly processes (see Table I), this paper implemented these techniques and applied them for the aforementioned case study. The table shows the implemented benchmark approaches and the results. The input features for the machine learning models are a flattened vector of all points deviations $d = Flatten ([x_d, y_d, z_d])$ while the outputs are the assembly process parameters $y$. Comparison is done on attributes namely, accuracy (MAE), goodness-of-fit ($R^2$), model complexity (number of trainable parameters) and training time. The hyperparameters of the comparison models were optimized using grid search. Tree-based models do not have trainable parameters although hyperparameters such as the number of estimators/trees and the model depth can be used to get a quantitative figure for model complexity. For statistical quantification of accuracy and goodness-of-fit, 20 runs of training and testing are conducted using a set of 2000 randomly sampled data points for training and 500 for validation within the validation range. The mean and standard deviation (SD) for each model-averaged across six process parameters have been reported. The model performance of the proposed OSER model is significantly better in terms of accuracy and goodness-of-fit. ANOVA followed by post-hoc Tukey-HSD test at 95% significance level considering two sources of variations (model type and process parameter) determines that the difference is significant. This comes at the expense of increased model complexity and training times.

**Fig. 7.** Performance under different levels of fault collinearity and multiplicity (from $y_1$, $y_2$, $y_3$ up to all parameters being simultaneously at fault $y_4, y_5, y_6$)

RCA with Uncertainty Quantification: As discussed in Section 1 the identified RCA frequently leads to costly corrective actions conducted in the manufacturing environment [11], therefore, it is crucial, especially for 6-sigma faults to have decision-driven RCA directed toward informing choices by uncertainty quantification of solving problems. The OSER methodology provides standard deviation of the predicted process parameter distributions $\sigma (y)$ that quantifies this uncertainty hence, fulfilling requirement (v). Although the performance of the OSER with 3D CNN and OSER with Bayesian 3D CNN models are similar, the latter can quantify and segregate the aleatoric and epistemic uncertainty while estimating the process parameters. To demonstrate the capability of the model in quantifying the uncertainty on unseen samples, evaluation is done on 500 samples outside of the training range (see Table I). The standard deviation across all observations has been averaged and compared for each process parameter $y_1, \ldots, y_6$. Results are shown in Fig. 8. The OSER with Bayesian 3D CNN model can quantify higher uncertainty in samples outside of training by an increased estimate for the standard deviations of the process parameters. Additionally, the uncertainty estimates enable adaptive sampling from the VRM simulator.

**Fig. 8.** Process Parameters Distribution Standard Deviations
2. OSER vs. currently used approaches at design phase when NO point cloud data is available – In manufacturing environments, the availability of a comprehensive dataset inclusive of all fault scenarios is not feasible, hence augmenting and enhancing the dataset with high-fidelity multi-physics simulation enables training and deployment of deep learning approaches during the design phase of a new productproduction system introduction. Given the proposed OSER approach transforms the simulation mesh nodes output and scanned point cloud output to the same voxelized point cloud that is compatible with 3D CNN, it enables this integration hence fulfilling Requirement (vi). This provides the capability for modelling and simulation of the assembly process and conducting system diagnosability and resilience analysis. Currently, no approaches are providing this capability for object shape error RCA at the design phase.

IV. CONCLUSION

This paper presented an Object Shape Error Response (OSER) approach which is relevant to manufacturing industries where dimensional and geometric variations can be quantified as object shape errors. This is also relevant to areas such as robotics, computer-aided detection, assembly, stamping, machining and additive manufacturing where RCA of dimensional variations translates to estimating the object shape error patterns and relating them to process parameters. Transfer learning can be leveraged for application in similar domains with exponentially lesser training samples [29]. The proposed approach leverages a Bayesian 3D CNN model trained within a closed-loop framework using a multi-physics simulation (VRM) model, to estimate shape errors and relate them to process parameters while quantifying uncertainty. This can then be deployed on real data collected from 3D scanners and thereby, enable more effective and efficient decision making for control and correction of manufacturing systems. The approach is benchmarked against state-of-the-art assembly RCA models and other machine learning models to highlight, statistically significant superior model performance while fulfilling the stated requirements. Leveraging such automated RCA models ensures early estimation and elimination of process variations before they become defects which can improve the quality and productivity of the system by reducing scrap and machine downtime. This also eliminates the need for a manual expert based trial and error approach for root causes analysis which is often ineffective and inefficient.

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