Integration of reconfigurable inspection with stream of variations methodology

Jacob Barhak*, Dragan Djurdjanovic, Patrick Spicer, Reuven Katz

NSF Engineering Research Center for Reconfigurable Manufacturing Systems, College of Engineering, University of Michigan,
2250 G.G. Brown Building, 2350 Hayward Street, Ann Arbor, MI 48109-2125, USA

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Abstract

This paper describes an advanced closed loop quality control methodology for reconfigurable manufacturing systems. The methodology enables rapid root-cause diagnostics for faster ramp-up of reconfigurable systems through integration of the Reconfigurable Inspection Machine (RIM) and the Stream of Variations (SoV) methodology. The RIM enables reconfigurable, rapid, and accurate inspection using non-contact sensors while the SoV methodology is used to quickly analyze the measurements and identify the root-cause of the errors produced during machining.

The feasibility of the industrial concept was experimentally validated. A machining error was introduced during machining of an engine head. Measurement information collected by the RIM was processed and used to locate the root-cause of the error using the SoV methodology.

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1. Introduction

Reconfigurable manufacturing systems (RMS) [1] are designed at the outset to economically produce products at high volume and to quickly accommodate changes in product designs and product demand within a family of parts. Reconfigurable systems are modular in structure, and accommodate change through the rearrangement of modules into different configurations. A typical operating scenario for such a system is to produce one or more products for several months and then be reconfigured so it can produce different products from the same family of parts.

When an RMS is reconfigured, even though designed for such changes, it is likely that there will be many quality problems to address as a result of the reconfiguration process. For example, with each module that is rearranged in the system, there are new opportunities for misalignments and subsequent dimensional errors. These quality problems cause system down time and slow the process of ramping-up to full production after reconfiguration. Hence, the rapid elimination of such quality errors is essential to the ramp up and operation of reconfigurable manufacturing systems and all high volume manufacturing systems in general.

Unfortunately, the present practices in quality control are not sufficient for reconfigurable manufacturing systems. Today, manufacturers employ highly flexible inspection machines (e.g. CMM’s) to reduce the cost of adapting to manufacturing changes. However, the inspection rates of these machines are much slower than production rates. This forces manufacturers to monitor quality by sampling parts off-line, on an infrequent basis. Thus, quality problems are often not detected until after a considerable number of defective parts have already been produced. The result is that defective parts occur repeatedly in batch quantities, which is quite disruptive and costly.

Furthermore, in the case of multi-station machining lines, the state of the art is that an experienced person is needed to help determine the source of the problem once a quality issue is detected. This is inefficient and costly, and it is not possible to quickly identify and repair the root-cause of the quality problem. The proposed methodology enables rapid root-cause diagnostics for faster ramp-up of reconfigurable systems through integration of the RIM and the SoV methodology.

The feasibility of the industrial concept was experimentally validated. A machining error was introduced during machining of an engine head. Measurement information collected by the RIM was processed and used to locate the root-cause of the error using the SoV methodology.

* Corresponding author. Tel.: +1 734 764 5291; fax: +1 734 615 0312.
E-mail address: jbarhak@umich.edu (J. Barhak).

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problem is detected. Until recently, no systematic root
cause identification methodologies existed to aid in this
process. In large-scale manufacturing systems, root-cause
identification is particularly difficult due to the system
complexity, especially in the case of systems that produce
complex machined components (e.g. engine heads). Such
systems produce parts with a large number of features in
many different stations with high-dimensional precision.
Without systematic root-cause identification methodo-
dies, much time is spent searching for the cause of
quality issues, which significantly increases the time to
ramp-up a reconfigurable system to full production capacity.

To help a complex RMS to quickly ramp-up to full
production after a change, a new and more powerful quality
control system is required. First, quality control must
include reconfigurable inspection machines that can change
as the manufacturing system changes. These inspection
machines must operate rapidly and accurately so that useful
inspection data can be collected without delay. Secondly,
quality control must include systematic root-cause diag-
nostic techniques to analyze the inspection information with
a model that can pinpoint the sources of dimensional errors.
Automating and integrating these two capabilities would
enable immediate corrective action on the production line,
thus significantly reducing the ramp-up time for reconfig-
urable systems [2]. This capability is not only necessary for
reconfigurable manufacturing systems, but is also of great
benefit in dedicated and flexible manufacturing systems as
well.

Recent development and maturing of non-contact
inspection capabilities [3,4] provide a solid foundation for
rapid inspection. Both laser sensors [3] and vision systems
[4] rapidly produce large amounts of accurate non-contact
measurements. The speed and accuracy of measurement
acquisition and processing opens the path for in-process
inspection that could dramatically decrease the number of
defective parts produced on the production line.

Non-contact measurement techniques were employed for
quality control in [5–9]. These techniques, however, are not
applicable to dimensional measurements of precision
machined complex parts (i.e. automotive engine heads and
blocks). Moreover, except in [5,6], existing techniques do
not provide root-cause identification of errors to close the
quality control loop.

In [10–12] researchers described a reconfigurable
inspection machine (RIM), which is designed to inspect a
family of engine cylinder heads. It is reconfigurable because
inspection sensors may be rearranged on the machine to
accommodate different automotive cylinder heads that must
be inspected. It is also rapid, because it employs several
non-contact sensors and is designed to perform inspections
at the same rate as a production line, which makes the RIM a
step towards 100% inspection of parts. Furthermore, the
RIM is highly accurate and able to inspect key features with
accuracy in the tens of microns [13]. These three
characteristics make the RIM very suitable for inspecting
parts in reconfigurable manufacturing systems.

Recent research advances have also resulted in methods
for successful modeling of dependencies between process-
level root-causes on one hand, and product quality on the
other hand. This is accomplished in the case of auto-body
assembly [14–17] and machining lines [18–21]. These
modeling tools allow explicit descriptions of the introduc-
tion, transformation, and propagation of workpiece errors as
they accumulate, station by station, in an assembly or
machining system. Subsequently, the models can be used to
rapidly identify process-level root-causes of manufacturing
errors based on measurements of the workpiece. Once the
root-causes are identified, product quality may be improved
through reduction of process variations [22–24]. Following
[2], this approach will be referred to in this paper as the Stream of Variation (SoV) methodology.

Previous to this work, rapid and accurate measurements
obtained through Optical Coordinate Measurement
Machines (OCMMs), have been processed by the SoV
methodology in order to identify the root-causes of auto-
body assembly variations [25]. In addition, SoV-based
methods have been applied in machining processes where
measurements were obtained from touch-probe Coordinate
Measurement Machines (CMMs) [23,26]. However, the
SoV methodology has never been combined with rapid and
accurate optical measurements in machining lines.

The introduction of the RIM concept provides an
alternative inspection device for use with the SoV
methodology allowing rapid inspection that is compatible
with Reconfigurable Manufacturing Systems. The concept
of the RIM enables reconfigurable, rapid, and accurate part
inspection in production environments, while the SoV
methodology enables rapid diagnostics of error sources for
defective parts. Compared to an off-line inspection
approach, this approach detects faulty parts quickly and
eliminates having scrap parts in batches. It also significantly
reduces the time to diagnose quality problems through the
use of systematic, SoV-based methods for identification of
root-causes of quality problems. Overall, the connection
between the RIM concept and the SoV methodology enables
an advanced closed-loop quality control process that is ideal
for Reconfigurable Manufacturing Systems (see Fig. 1).

To this end, this paper proposes and demonstrates the
integration of a prototype RIM and the SoV methodology
for the quality control of machined engine heads. The RIM
rapidly inspects engine heads and its measurements are then
evaluated by the SoV methodology in order to identify the
root-causes of dimensional errors.

The paper first discusses the RIM prototype and its
capabilities in Section 2. Then the SoV modeling method-
ology is briefly described in Section 3, while Section 4
provides information on how a linear state-space SoV model
can be used to identify root-causes of manufacturing errors.
Section 5 explains how RIM measurements are processed
for the purpose of interfacing with the SoV. An example of
2. The reconfigurable inspection machine (RIM)

Reconfigurable Manufacturing Systems can economically accommodate production of several products from a part family. This efficiency is achieved by providing just enough functionality to handle changes within the part family while taking advantage of the similarities within the part family. This type of production system requires modular diagnostics that can accommodate the entire part family. Within this economical framework, a RIM provides these requirements better than other inspection technologies.

In the case of this work, a RIM has been designed to inspect a part family of engine cylinder heads, and this RIM is hereafter referred to as ‘the RIM’. An automotive engine cylinder head (such as the one shown in Fig. 2) is a complex workpiece involving numerous machining operations in which a number of different features are machined. Engine head quality is important since it is a key component in internal combustion engines, having interaction with other high-precision components. High precision is necessary since inaccuracies generated during machining may cause overly loose or tight fits, which could result in poor performance. Since an engine head has many different machined features and it requires high precision, the engine cylinder head is a good test case for rapid high-precision inspection.

Like other reconfigurable machines, the RIM sensor array (Fig. 3) can be reconfigured to adapt to the limited product changes within the part family of engine heads. To this end, the RIM employs non-contact measurement sensors, including a vision system and several laser probes. The laser probes can accurately measure 3D features, while the vision system captures 2D images of the engine head surface.

In comparison to a typical CMM which has a single contact probe for data acquisition, the RIM has a high inspection throughput since it can acquire large amounts of measurement data rapidly, through simultaneous operation of multiple non-contact sensors. For instance, each laser probe is capable of storing 7000 points at a rate of 750 measured points per second.

In addition to high acquisition rate, high accuracy is maintained during measurement. The part location is determined by a high precision linear scale with 2 µm accuracy as it moves past the laser probes. Each laser probe can measure a set of points along the engine head surface with accuracy better than 3 µm and with 1 µm repeatability. The measured part moves past the vision system as well during inspection. The vision system acquires an image of the part surface by using a line scan camera that assembles...
image columns. The image resolution is 4096 pixels vertically and the image columns are typically collected at the rate of 682 scan lines per second. The acquired image has a typical resolution of 44 μm per pixel, with the possibility to, when necessary, increase the resolution up to 4.8 μm, depending on the field of view parameters.

Such abundance of inspection information allows the measurement of many types of geometric dimensions, including surface flatness, hole diameters, distances between holes, distance and orientation between surfaces, etc.

During measurement extraction, the acquired inspection information is corrected using several alignment procedures starting with calibration, for which procedures were established in [27]. The calibration procedure first requires measurement of a reference part of known dimensions. Afterwards, alignment operations establish a common coordinate system for the representation of the laser measured points. This allows the measurements to be produced in a format that can be interpreted by the existing SoV model of machining lines.

3. The stream of variations methodology

Most modern manufacturing systems are multi-station systems involving a large number of operations performed on multiple manufacturing stations. Each manufacturing station introduces errors that propagate through the system and influence the final product quality. As indicated in Fig. 4, product quality errors \( x(k-1) \) accumulated in manufacturing stations \( 1,2,3,\ldots,k-1 \) influence the product quality errors that are present after operations at manufacturing station \( k \). Furthermore, at any manufacturing station \( k \), new errors \( u(k) \) are introduced and also influence the outgoing product quality \( x(k) \). Measurements \( y(k) \) of the part quality can potentially be taken after operations at any station in order to depict the outgoing part quality. One should note that the inherent natural process variation \( W(k) \) also contributes to the product quality errors \( x(k) \) and thus also appears in the measured quality characteristics \( y(k) \).

Reduction and elimination of the root-causes \( u(k) \) of quality problems that are introduced and accumulated in each manufacturing station \( k=1,2,\ldots,N \) would lead to a reduction and elimination of the quality problems in the finished workpiece. Nevertheless, in traditional product-oriented quality control, measurements are taken only to establish whether the outgoing product quality is within the manufacturing specifications. In the recently developed process-oriented quality control approach, the goal of taking measurements is to identify and quantify the root-causes \( u(k), k=1,2,\ldots,N \) that contribute to the quality problems. Fast and accurate identification of the root-causes of quality problems would lead to a fast and efficient reduction and/or elimination of these problems and thus, a faster ramp up of manufacturing lines, as well as a higher level of product quality.

In order to perform this task, a model must exist connecting the root-causes \( u(k) \) of the quality problems with the measured part quality characteristics \( y(k) \). The problem of modeling and reduction of dimensional variations in automotive body assembly was addressed in [28–31] through their analytical modeling and pattern recognition. This problem was also addressed in [2] where the author suggested to explicitly model the flow and transformation of dimensional errors in assembly lines from one station to the next one, resulting in the state-space SoV form of the model.

A linear state space model of dimensional errors in automobile assembly lines was derived in [14] and improved in [15,16], using the assembly station index as the time parameter in the model. Recent research resulted in a series of analytical modeling tools pertaining to dimensional

![Fig. 3. The RIM and its systems.](image-url)
where $V$ errors in multi-station machining systems [18–21]. In [14,15,19–21], the assumptions of small errors of product parameters $x(k)$ led to linearized connections between the root-causes of quality problems $u(k)$ and the product quality $x(k-1)$ arriving from the previous manufacturing station, which can be expressed in the linear state-space form of a system equation

$$x(k) = A(k)x(k-1) + B(k)u(k) + W(k)$$

(1)

where $W(k)$ denotes the modeling noise due to linearization and unmodeled effects. In addition, the connection between the part quality $x(k)$ exiting the manufacturing station $k$ and the root-causes $u(k)$ of quality errors in station $k$ with the measured part quality $y(k)$ can be expressed in the linear form of an output equation

$$y(k) = C(k)x(k) + D(k)u(k) + V(k)$$

(2)

where $V(k)$ denotes a noise term due to sensor noise, linearization and unmodeled effects. Eqs. (1) and (2) represent the system and output equations, respectively, of a linear state-space SOV model that represents the flow of product quality errors as a linear discrete time-varying (DTV) system [32], where the role of the time index is played by the manufacturing (machining or assembly) station index $k$. Matrices $A(k)$ describe how machining errors accumulated up to and including operation $k-1$ are transformed and influence errors in machining operation $k$, while matrices $B(k)$ describe how new errors are introduced into the workpiece at operation $k$. Matrices $C(k)$ connect errors of the workpiece CAD parameters expressed in vectors $x(k)$ to the measured errors expressed in vectors $y(k)$, while matrices $D(k)$, which exist only in the case of on-machine measurements [19,20], describe how machining errors introduced in machining operation $k$ directly influence the measured errors $y(k)$. The special form of these models allowed incorporation of a vast knowledge of control theory and multivariate statistics to be employed in solving problems in multi-station assembly and machining quality.

In most cases, analytical models of dimensional assembly errors have been employed to accomplish identification and classification of root-causes of manufacturing errors [17,18,22–25,28–31]. Also, analytical models have been utilized to achieve formal characterization [26,33–35] and optimal selection of measurements and sensor locations [36–38]. In addition, Mantripragada and Whitney [39] derived a state-transition model of variation propagation in assembly lines and utilized the special form of that model to achieve optimal control of assembly variations.

In this paper, the focus will be placed on facilitating simultaneous use of rapid and accurate optical measurements obtained through the RIM and the SOV based identification of root-causes of dimensional machining errors using the RIM measurements. A description of the SOV model based identification of root-causes of dimensional machining errors is given in the next section, prior to describing the RIM interface with the SoV in Section 5.

4. Identification of root-causes of quality faults based on SOV methodology

The linear state space model (1) and (2) describes how machining errors are introduced, transformed and accumulated as a workpiece is being machined in a multi-station machining system. In the existing SoV models of machining processes presented in [18–21], each workpiece feature was described by its position, orientation and a set of scalar parameters, such as the cylinder diameter, hole diameter and depth, slot width and depth, etc. The feature positions and orientations were expressed in a coordinate system determined by selected workpiece measurement datum features, and the state vector $x(k)$ from the model (1) and (2) comprised of errors in positions, orientations and scalar parameters of each workpiece feature after machining operation $k$. The ‘input’ vectors $u(k)$ contain errors in fixture parameters and errors in parameters of the newly machined surfaces at machining operation $k$. Such errors in orientation, position and scalar parameters (diameters of holes, slot depths, etc.) of the newly machined surfaces could occur due to thermal effects, tool wear, or other error causes. Nevertheless, the existing SoV models of multi-station machining are not able to represent the dependency of error parameters of the newly machined surfaces on other process parameters, such as tool wear or thermal errors. Further identification of thermal and tool-path related errors would have to be accomplished through other methods, such as thermal error, or tool wear monitoring.

Simple manipulations of Eqs. (1) and (2) for $k=1,2,...,N$ yield

$$[y(1) \ y(2) \ \cdots \ y(N)]^T = T[u(1) \ u(2) \ \cdots \ u(N)]^T + \epsilon$$

(3)

where

$$T = \begin{bmatrix}
M_{1,1} & 0 & \cdots & 0 \\
M_{2,1} & M_{2,2} & \cdots & 0 \\
& & \ddots & \vdots \\
M_{N,1} & M_{N,2} & \cdots & M_{N,N}
\end{bmatrix}$$

(4)

$$M_{ij} = \begin{cases}
C(i)\Phi(i,i)B(i) + D(i), & i = j \\
C(i)\Phi(i,j)B(j), & i > j
\end{cases}$$

for the matrices $M_{ij}$. The matrices $B(i)$ and $D(i)$ are the matrices of the linear system with $C(i)$ and $D(i)$ being the matrices of the linear system with $C$ and $D$ denoting the matrices of the linear system with $C$ and $D$.
and

\[
\epsilon = \begin{bmatrix}
\tilde{M}_{1,1} & 0 & \cdots & 0 \\
\tilde{M}_{2,1} & \tilde{M}_{2,2} & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
\tilde{M}_{N,1} & \tilde{M}_{N,2} & \cdots & \tilde{M}_{N,N}
\end{bmatrix}
\begin{bmatrix}
W(1) \\
W(2) \\
\vdots \\
W(N)
\end{bmatrix}
+ \begin{bmatrix}
V(1) \\
V(2) \\
\vdots \\
V(N)
\end{bmatrix},
\]

(5)

\[
\tilde{M}_{ij} = C(i)\Phi(i,j), \ i \geq j
\]

Matrices \( \Phi(k_1,k_2), k_1,k_2=1,2,\ldots,N \) are the discrete-time state transition matrices [32], satisfying

\[
\Phi(k_1,k_2) = \begin{cases}
A(k_2 + 1)A(k_2 + 2)\cdots A(k_1) & \text{for } k_1 > k_2 \\
I & \text{for } k_1 = k_2
\end{cases}
\]

Introducing the notation

\[
Y = \begin{bmatrix}
y^T(1) \\
y^T(2) \\
\vdots \\
y^T(N)
\end{bmatrix};
\]

(6)

\[
U = \begin{bmatrix}
u^T(1) \\
u^T(2) \\
\vdots \\
u^T(N)
\end{bmatrix}
\]

and viewing \( \epsilon \) as the noise term, Eq. (3) becomes a linear model

\[
Y = TU + \epsilon
\]

(7)

(8)

connecting the measured dimensional errors \( Y \) with their root-causes \( U \).

The problem of identification of root-causes of dimensional machining errors now reduces to estimating elements of the vector \( U \) of root-causes of dimensional machining errors out of measured dimensional errors \( Y \) of the workpiece. A number of methods for estimating parameters of the root-causes out of the linear model (8) have been reported in the literature, including pattern matching applicable to only single faults [18], Linear Least Square Estimation (LLSE) [34], Robust Linear Estimation (RLE) [35], and Minimum Norm Quadratic Unbiased Estimation (MINQUE) from linear mixed models [23]. More recently, Wang et al. [24] reported a ‘fixture equivalency’ method of reducing the dimension of the root-causes vector \( U \) in the linear model (8) in order to make the regression matrix \( T \) become a full rank matrix, in which case a simple Least Squares (LSQ) solution of a system of linear Eq. (8) can be employed to estimate vector \( U \) out of each measurement vector \( Y \).

In all previously published work pertaining to the use of SoV methodology in identification of root-causes of machining errors, measurements of the workpiece were obtained using traditional, touch-probe Coordinate Measurement Machines (CMMs) [18–24,26], and no attention was dedicated to facilitating the use of the SoV methodology in conjunction with modern non-contact measurement devices, such as the RIM described in Section 2. Considering the higher speed and accuracy of the RIM over the currently available, traditional measurement technologies in machining, as described in Section 2, it is desirable to facilitate root-cause identification based on Eq. (8), using measurements obtained from the RIM. Incorporation of RIM measurements into the SoV based identification of root-causes of automotive cylinder head quality problems will be described in Section 5.

5. Integration of RIM measurements and the SoV methodology

A key aspect of the quality of a work piece is defined by the mutual relationships among work piece features (parallelism between faces, distances between holes, etc.). In order to express the relationships among workpiece features for the SoV methodology, dimensional measurements are expressed with respect to the part coordinate system. The part coordinate system is defined by specific datum features on the workpiece, which are in turn defined by the part design. However, each laser probe on the RIM obtains measurements of workpiece features in the probe’s own coordinate system. Therefore, in order to use RIM measurements within the SoV methodology, the RIM measurements of the work piece have to be transformed to the part coordinate system. This section will describe all the procedures that measurement data undergoes from filtering through alignment and up to output for the SoV methodology. Fig. 5 demonstrates the main procedures and their order.

Calibration data and procedures are required only during RIM reconfiguration. The output of the calibration procedures can be stored and used later as pre-processed data. In contrast, measurements and computations for engine heads are performed for each inspected part. The majority of the computations involve calculations required to align the data to the desired coordinate system. For this, a least squares (LSQ) routine is employed from a procedure library.

Before applying the various calibration and inspection procedures to the family of engine heads, several coordinate systems should be defined. The coordinate systems are presented in Fig. 6 and described below:

- Joint face coordinate system \((X_i,Y_i,Z_i)\). A coordinate system in which is used to represent raw data collected by the laser probes aimed at the joint face of the part.
- Cover face coordinate system \((X_c,Y_c,Z_c)\). Represents raw data collected by the laser probes on the cover face of the part.
- Machine coordinate system \((X_m,Y_m,Z_m)\). A coordinate system established after calibration. It enables representation of data collected on both joint and cover faces in a single 3D coordinate system.
- Vision coordinate system \((X_v,Y_v,Z_v)\). A coordinate system established by the vision system viewing the joint face of the part.
- Part coordinate system \((X_p,Y_p,Z_p)\). The part coordinate system is defined by the actual measurement datum features of the workpiece that define the coordinate system in which the measurements are expressed. In this
work it is defined by the joint face and two locator holes on the joint face side of the cylinder head.

The following sections will briefly describe the computations performed in order to represent the measurements in the part coordinate system as described in Fig. 5.

5.1. Filter probe data

This procedure is used to filter probe data supplied by laser sensors and the linear scale. Each point measured by the laser probe is accompanied with a signal to noise ratio (SNR) value that is used against a threshold value in our filtering procedure. Further filtering removes undesirable features such as hole

Fig. 5. The data flow of the RIM measurement information through different calibration and alignment procedures.

Fig. 6. Coordinate systems in the RIM: part (p), machine (m), joint face (j), cover face (c) and vision system (v). Each coordinate system is marked with a corresponding letter. Two locator holes with centers $o_1$ and $o_2$ help define the part coordinate system.
chamfers. As a byproduct, the filtering procedure identifies hole edges that are used later to calculate hole centers (Fig. 7).

5.2. Calculate sensor placement compensation parameters

The laser sensors can be placed at different distances from the measured part and from the beginning of the linear scale (Fig. 8). This procedure calculates the constants that compensate for the relative misalignment of the sensors in the \( X \) and \( Z \) directions relative to the surface of the reference part as suggested in [27] where the known shape of the reference part allows extracting the compensation values as part of the calibration process.

5.3. ‘Virtual ball’ interpretation

Laser measurements have different characteristics than a Coordinate Measurement Machine (CMM) employing a contact probe. As a result, the measurements reported will differ between the two measurement methods (Fig. 9).

The ‘virtual ball’ method [40] is a geometrical interpretation method from laser measurements to values that would have been measured by a contact probe.

5.4. Flatness and normal calculation procedure

The flatness and normal of a surface are byproducts of using a least square (LSQ) technique to fit a best fit plane to the measured points. The procedure finds the best fit plane minimizing the squared \( Z \) distance of the points from the plane. The procedure can also act as a statistical filter for outlier points outside an acceptable zone taking into account the standard deviation of the data. This procedure is used as a library procedure for several alignment procedures described in Sections 5.5–5.7.

5.5. Calculate laser system transformations to machine coordinate system

This procedure allows representation of the data collected by all laser probes in a single 3D coordinate system. The machine coordinate system is established upon calibration using the reference part.
Basically, the procedure uses the known shape of the reference part to align the measurement data in 3D. The alignment matrices $M_{\text{Ref-joint}\rightarrow \text{machine}}$ and $M_{\text{Ref-cover}\rightarrow \text{machine}}$ are the main output of the procedure (details are provided in [41]). Those matrices enable any subsequent measurement to be represented in 3D space in homogeneous coordinate systems. Eqs. (9) and (10) present the transformations for points collected by probes on the joint and cover faces, respectively, to points in a single coordinate system regardless of probe positioning.

$$p_{\text{Joint}} = M_{\text{Ref-joint}\rightarrow \text{machine}} \begin{bmatrix} x_{\text{Joint}} \\ y_{\text{Joint}} \\ z_{\text{Joint}} \end{bmatrix}$$ (9)

$$p_{\text{Cover}} = M_{\text{Ref-cover}\rightarrow \text{machine}} \begin{bmatrix} x_{\text{Cover}} \\ y_{\text{Cover}} \\ z_{\text{Cover}} \end{bmatrix}$$ (10)

### 5.6. Calculate transformations to part coordinate system

This procedure concludes the alignment efforts by calculating the transformation from the machine coordinate system to the part coordinate system as required by the SoV. The transformation is established by considering the best fit plane fitted to the joint face measurements in conjunction with the previously calculated center of the locator holes (Section 5.1). When the transformation matrix $M_{\text{machine}\rightarrow \text{part}}$ is established (see [41]) any point in the machine coordinate system can then be transformed to the part coordinate system as depicted in (11)

$$p_{\text{Part}} = M_{\text{machine}\rightarrow \text{part}} p_{\text{Machine}}$$ (11)

The transformation matrix is then applied to the measured data in order to aid in dimension extraction. It also enables the extraction of parameters required by the SoV as input—namely a point on the cover face and its normal in the part coordinate system.

### 5.7. Calculate dimensions and tolerances

This procedure calculates dimension, tolerance, flatness and parallelism of the cylinder engine head. Since the measured points are presented in the part coordinate system it already defines the joint face as the datum. Thus, parallelism is easily calculated. The distance between the joint face and cover face can be calculated using average distances (Fig. 10). Additional information can be found in [41].

### 5.8. Root-cause identification using the stream of variation model

The orientations, positions and scalar parameters describing the workpiece features measured on the RIM and obtained using the methods described in Sections 5.1–5.6 are components of a vector of measurements $Y$ that can be interpreted by the existing SoV models of machining lines. This vector of measurements can thus be ultimately used for the SoV based identification of root-causes of dimensional variations.

![Fig. 9. A ball in contact with a surface compared to laser measurement at the same x value.](image)

![Fig. 10. Calculation of flatness, parallelism and dimension with tolerance values.](image)
machining errors through an adequate estimation of the vector $U$ in the linear model (8).

6. Results

This section provides results from the experimental validation of the integration between the RIM technology and the SoV-based identification of process-level root-causes of machining errors. Experimental validation and demonstration was conducted in the machining process for the cylinder head shown in Fig. 2. The machining process is used by a major automotive manufacturer and consisted of five machining operations executed in three fixturing setups. The machined features and fixturing setups are summarized in Table 1.

The experiment involved two parts, referred to as Parts A and B, machined after errors were intentionally inserted into the process. In the case of Part A, the error was induced by introducing a 1.05 mm shim under one of the locating pins in the fixture used in Setup 2 (locating pin $L_3$ indicated in Fig. 11 that shows the fixture used in Setup 2 of the cylinder head machining process). In Part B, the error was introduced by offsetting the cutting tool that milled the Joint Face (J) by 500 $\mu$m (machining operation no. 2).

The machined parts were measured by the RIM laser system that acquired close to 9000 points in a line pattern shown in Fig. 12. Information about the location and diameter of the holes was derived from the vision system to allow transformation of the acquired measurements into the part coordinate system defined by the measurement datum features of the workpiece. The RIM data was transformed into the vectorial feature representation format used by the SoV modeling, in which each feature is represented by its orientation vector expressed in the part coordinate system, position vector expressed in the part coordinate system and a set of scalar parameters describing that feature. This representation of the RIM measurements enables mapping of the measured workpiece parameters into the corresponding process-level faults using the SoV model of the process. Table 2 shows the measurement information obtained from Parts A and B using the RIM, including the orientation and position vectors of the measured features, expressed in the part coordinate system defined by the measurement datum features of the workpiece.

Table 3 shows the orientations and positions of the Cover Face obtained using a CMM and using the RIM. It also

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Table 1

<table>
<thead>
<tr>
<th>Setup</th>
<th>Locating surfaces</th>
<th>Operations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Setup 1</td>
<td>Primary: Raw Datum X1, X2 and X3; Secondary: Raw Datum Y1 and Y2; Tertiary: Raw Datum Z1;</td>
<td>Mill the Cover Face (CF)</td>
</tr>
<tr>
<td>Setup 2</td>
<td>Primary: Machined Cover Face (CF); Secondary: Raw Datum Y1 and Y2; Tertiary: Raw Datum Z1;</td>
<td>Mill the Joint Face (J) Drill the Cylinder B Drill the Cylinder C</td>
</tr>
<tr>
<td>Setup 3</td>
<td>Primary: Machined Joint Face (J); Secondary: Machined Cylinder B; Tertiary: Machined Cylinder C;</td>
<td>Mill the Slot S</td>
</tr>
</tbody>
</table>

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Fig. 11. Fixture used to hold the workpiece during milling of the Joint Face in the Setup 2.

Fig. 12. Information derived by the laser system mounted on the RIM: (a) raw data individually collected by the four laser probes in their coordinate systems. (b) The processed data transformed to part coordinate system.
shows the offsets of the three locating pins in the fixture used in Setup 2, as identified through application of the SoV model-based equivalent fixturing method on the measurements obtained using the CMM and the RIM.

From Table 3 one can see that both the CMM and RIM devices gave similar measurement and diagnostic results. In the case of Part A, one can clearly see that the Locating Pin \( L_3 \) in the Setup 2 fixture is significantly higher than the other two pins in that fixture, which is consistent with the fact that a 1.05 mm shim was placed under the Locating Pin \( L_3 \) of the Setup 2 fixture. In the case of Part B, again both the CMM and RIM measurements indicate similar results. For Part B, diagnostic results indicate a similar offset in all three locating pins in Setup 2. This is consistent with the tool offset considering that the equivalent fixturing method [24] identifies the equivalent patterns of fixture parameter deviations that caused a given workpiece quality deviation and considering the fact that the deeper cut inside the cylinder head is equivalent to the effect of the three fixture pins \( L_1, L_2 \) and \( L_3 \) in the Setup 2 fixture being higher by the same amount (500 \( \mu m \)).

In addition, Table 3 shows that the height of the shim and the tool offset were somewhat underestimated (around 10% in the case of Part A and around 12% in the case of part B), regardless of whether the RIM or CMM measurements were used for the diagnosis. The reason for this difference is most

<table>
<thead>
<tr>
<th>Part</th>
<th>RIM measurements</th>
<th>Information passed to SoV in the part coordinate system</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Position on the cover face</td>
<td>Orientation of the cover face</td>
</tr>
<tr>
<td>Part A</td>
<td>Width 119,004 mm</td>
<td>( p_x ) 300.2594 ( n_x ) -0.00040</td>
</tr>
<tr>
<td></td>
<td>Parallelism 1153 ( \mu m )</td>
<td>( p_y ) -43.6667 ( n_y ) 0.00520</td>
</tr>
<tr>
<td></td>
<td>Joint face flatness 31 ( \mu m )</td>
<td>( p_z ) 119.6088 ( n_z ) 1.0000</td>
</tr>
<tr>
<td></td>
<td>Cover face flatness 30 ( \mu m )</td>
<td></td>
</tr>
<tr>
<td>Part B</td>
<td>Width 119,097 mm</td>
<td>( p_x ) 269.4127 ( n_x ) -0.00001</td>
</tr>
<tr>
<td></td>
<td>Parallelism 63 ( \mu m )</td>
<td>( p_y ) -44.2740 ( n_y ) 0.00020</td>
</tr>
<tr>
<td></td>
<td>Joint face flatness 30 ( \mu m )</td>
<td>( p_z ) 119.1211 ( n_z ) 1.0000</td>
</tr>
<tr>
<td></td>
<td>Cover face flatness 19 ( \mu m )</td>
<td></td>
</tr>
</tbody>
</table>

Theoretical offsets of workpiece CAD parameters and locating pins based on the measurements of the shim that was placed in the fixture (Part A) and the tool offset (Part B) are also enclosed (columns corresponding to 'Theoretical shifts in part CAD parameters' and 'Theoretical locating pin offsets').
likely due to the fact that the cutting process close to the location of the shim, as well as in the case with the additional tool offset, resulted in an increased depth of cut. The increased depth of cut caused the tool to deflect somewhat and subsequently reduce the amount of material removed from the work piece. In addition, the thickness of the shim may have reduced during clamping and cutting due to compressive forces. These errors were not taken into account by the model and caused even more difference between the estimated height of the locating pin $L_3$ (Part A) and the height of the shim measured before it was placed under the locating pin $L_3$ [19].

Furthermore, one can also notice that discrepancies between the expected locating pin offsets (diagnostic results given in the rightmost column of Table 3, obtained based on the direct measurements of the shim placed under the locating pin $L_3$ and based on the nominal tools offset of 500 µm) and locating pin offsets obtained using RIM measurements are smaller than those observed between the expected locating pin offsets and the locating pin offsets obtained from the CMM measurements, especially in the case of Part A. This observation supports the conjecture that besides being attainable in a shorter amount of time, the RIM measurements are more accurate and reliable than those obtained using a CMM.

In spite of the apparent discrepancies due to the unmodeled effects and linearization errors, which could be better described if multiple workpieces were machined under the same conditions in order to describe the natural variations of the process and modeling noise, the errors in estimating the locating pin and tool offsets are relatively small compared to the nominal size of the errors that were introduced. This is why one can conclude that the results shown in this section demonstrate feasibility and effectiveness of utilizing optical measurements obtained through the RIM in order to obtain diagnostic information through the use of the SoV methodology.

7. Conclusions and future work

This paper presents an integration of two systems: the RIM and the SoV methodology. Each of these alone improves the performance of the quality control of a manufacturing system. The RIM facilitates the gathering of large amounts of measurement data accurately and rapidly at production line rates, while the SoV methodology provides diagnostic capabilities to close the quality control loop. When both are combined together, a responsive closed loop quality control system is attained.

This type of quality control is important for Reconfigurable Manufacturing Systems. In RMSs a flexible all-purpose CMM may be inappropriate from a financial point of view.

The RIM and the SoV methodology were combined conceptually and practically. Experimental validation proved the concept on complex precision machine parts.

Future work will concentrate on extending the RIM capabilities to perform a wider variety of inspections by including more three-dimensional measurements of machined part features for diagnostics at production line rates.

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References


