Available online at www.sciencedirect.com

ScienceDirect

Procedia CIRP 72 (2018) 503–508

www.elsevier.com/locate/procedia

51st CIRP Conference on Manufacturing Systems

# Cyber-Physical Manufacturing Metrology Model ($CPM^3$) – Big Data Analytics Issue

Vidosav Majstorovic[a]*, Slavenko Stojadinovic[a], Zivana Jakovljevic[a], Srdjan Zivkovic[b], Dragan Djurdjanovic[c], Julija Kostic[a], Nemanja Gligorijevic[a]

[a]*University of Belgrade, Faculty of Mechanical Engineering, Belgrade, Serbia*
[b]*Military Technical Institute, Coordinate Metrology Lab, Belgrade, Serbia*
[c]*Department of Mechanical Engineering, University of Texas, Austin, TX, USA*

* Corresponding author. Tel.: + 381 11 33 02 407; fax: +381 11 33 70 364. *E-mail address:* vidosav.majstorovic@sbb.rs

**Abstract**

Internet of Things (IoT) is changing the world, and therefore the application of ICT (Information and Communication Technology) in manufacturing. As a paradigm based on the Internet, IoT utilizes the benefits of interrelated technologies/smart devices such as RFID (Radio Frequency Identification) and WSAN (Wireless Sensor and Actuator Networks) for the retrieval and exchange of information thus opening up new possibilities for integration of manufacturing system and its cyber representation through Cyber-Physical Manufacturing (CPM) model. On the other hand, CPM and digital manufacturing represent the key elements for implementation of Industry 4.0 and backbone for "smart factory" generation. Interconnected smart devices generate huge databases (big data), so that Cloud computing becomes indispensable tool to support the CPM. In addition, CPM has an extremely expressed requirement for better control, monitoring and data management. Limitations still exist in storages, networks and computers, as well as in the tools for complex data analysis, detection of its structure and retrieval of useful information.
Products, resources, and processes within smart factory are realized and controlled through CPM model. In this context, our recent research efforts in the field of quality control and manufacturing metrology are directed to the development of framework for Cyber-Physical Manufacturing Metrology Model ($CPM^3$). $CPM^3$ framework will be based on: 1) integration of digital product metrology information obtained from big data using BDA (big data analytics) through metrology features recognition, and 2) generation of global/local inspection plan for CMM (Coordinate Measuring Machine) from extracted information. This paper will present recent results of our research on $CPM^3$ – big data analytics issue.


Peer-review under responsibility of the scientific committee of the 51st CIRP Conference on Manufacturing Systems.

*Keywords:* Cyber-Physical Manufacturing, CMM, Modelling, Big data Analytics

## 1. Introduction

Cyber Physical Manufacturing Systems (CPMS) are based on integration and interconnection of Cyber-Physical Systems (CPS) using Internet of Things (IoT) and cloud technologies. They represent high-tech methodology for development of new generation of factories with ever increasing intelligence, flexibility and self-adaptability. CPMS generate high quantity of data through horizontal integration (value added networks), as well as through functional hierarchy of the resources [1]. The data has to be analytically processed and utilized for CPMS/CPS control. In these purposes two functional entities are necessary: (a) reliable connectivity that ensures real-time data acquisition from the physical world as well as real-time information feedback from the cyber space, and (b) intelligent data management and analytics within cyber space [2]. Five levels – 5C CPS architecture for Industry 4.0 manufacturing systems includes the following functions [3], [4]: (a) smart connection – acquisition of accurate and reliable data from process at the low control level using sensors, as well as from

2212-8271 © 2018 The Authors. Published by Elsevier B.V.
Peer-review under responsibility of the scientific committee of the 51st CIRP Conference on Manufacturing Systems.
10.1016/j.procir.2018.03.091

the shop-floor controllers and their transfer to servers, (b) data-to-information conversion – at this level previously acquired data are analyzed and transformed into useful information that represent the basis for intelligent control, (c) cyber level – central information hub of the 5C architecture which receives high quantity of data and immediately analyzes them, and makes data base regarding current and previous states of the CMS (twin model, clustering and data mining) [4], (d) cognition level – at this level the knowledge for supervision, control and decision making is generated based on information from previous levels, and (e) configuration level where the feedback information from cyber space is generated; feedback information makes a basis for self-configuration and self-adaptability of machines in the physical world.

In the presented 5C CPS architecture [3] in-process quality control represents key asset. Namely, modern understanding of measurements of quality in manufacturing is that their purpose is to enable adequate monitoring and tracking relevant process parameters, based on which any deviations away from their nominal behavior can be corrected via manual intervention, or automatically. Development of CPS offers new opportunities to accomplish this function via detailed models (ideally, "twin models") of the underlying process and product. Timely generation of these models requires extraction of useful information from bulk data using big data analytics and different data mining methods. The increasing role of big data leads to continuous growth of research in these fields including [6 7]: (a) machine learning methods such as different kinds of regression (support vector machines, neural networks, ANOVA) to gain insight into trends within the data, (b) pattern recognition methods including supervised classification and clustering, which structure big data sets, and (c) expert knowledge, for example using a lookup table.

Generation of detailed process models from quality measurements in manufacturing requires the development of dedicated framework. To address this issue, we have put our recent research efforts into the development of Cyber-Physical Manufacturing Metrology Model (CPM$^3$) [8]. During test implementation of CPM$^3$, we have encountered the generation of a number of big data sets that required processing, finding of correlations between data and its structure as well as the extraction of useful information to be shared between CPM$^3$ modules. In this paper we summarize some of the results in the implementation of big data analytics in CPM$^3$ data sets.

The reminder of the paper is structured as follows. In Section 2 we analyze the role of in-process measurements in CPMS and related research work in the field. Section 3 presents CPM$^3$ model, its data sets and big data analytics within this model. Finally, in Section 4 we provide concluding remarks and future work guidelines.

## 2. In-process measurements in CMS

In-process measurements represent the backbone of the CPMS and in particular in the generation of digital twins of manufacturing processes and resources. In [7], it was originally suggested that process/product models can be utilized for identification of root causes of problems in the product quality. The early works focused on dealing with the multi-stage character of manufacturing processes, where process parameters in one stage affect the quality in the downstream stages, resulting in often highly complex, nonlinear dependencies between process parameters and measurements of product quality [9]-[15]

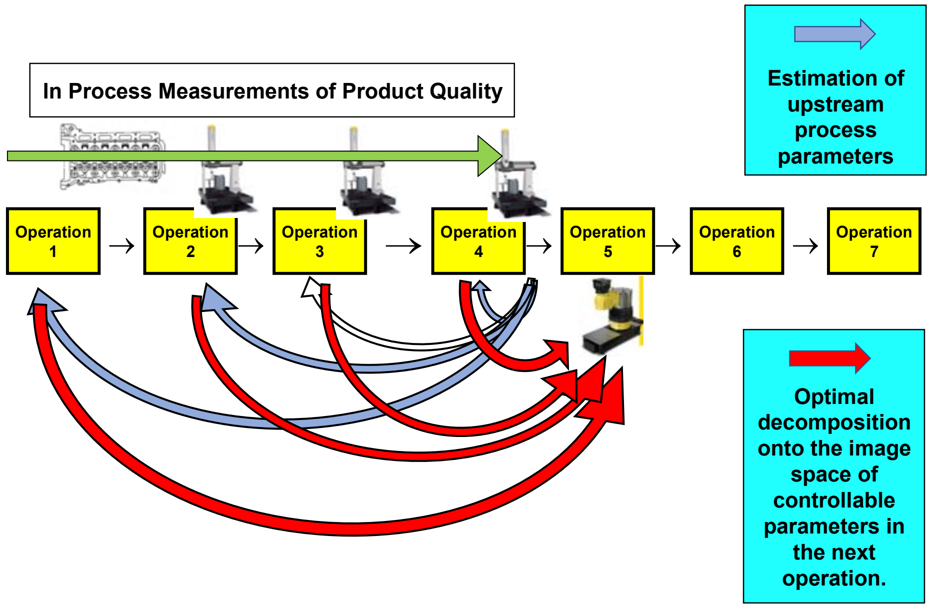



Fig. 1. Model based active control of process quality based on in-process measurements of the product and cyber-physical model of the error flow in the manufacturing process.

The focus was on pursuing and exploiting a state space model form where role of the time index was played by the operation index, and coupling that form with advanced statistical estimation techniques to realize inverse mapping from quality measurements into the space of process parameters. The emphasis on the tractability of linear state space model form led to applications being limited to sheet-metal assembly and machining of prismatic parts, where kinematic effects and very simple part compliance effects could be modeled [16]-[18].

More recent work led to more elaborate utilization of the state space form of the model to realize on-line automatic compensation of quality errors based on in-process measurements of the workpiece [19]-[21]. Namely, modern manufacturing processes, such as manufacturing of semiconductor microelectronics, or roll-to-roll manufacturing, have a number of on-line adjustable process parameters that can be automatically adapted to counteract whatever quality problems are perceived in the process, as well as increased amounts of in-process measurements that give one unprecedented transparency into the process. In such an environment, at any stage of the manufacturing process, in-process measurements collected up to that manufacturing stage can be used to estimate upstream process parameters via an inverse of the cyber-physical model of the flow of errors in the system (similarly to what we see in the early works in [9]-[15]), which can then be used to predict effects of those parameters in the downstream operations and counteract those effects via controllable parameters in those operations (as illustrated in Fig. 1). As the manufacturing process progresses and as the workpiece moves through the system, the estimation of upstream process parameters and compensation of their effects via controllable parameters in the downstream operations continues, thus enabling continuous and intelligent utilization of often enormous amounts of data collected through in-process measurements.

This paradigm was theoretically demonstrated using models of machining of prismatic automotive parts [19], [20], and lithography overlay in semiconductor manufacturing [22]. Incorporation of robustness to model and noise uncertainties, as enabled by the methods described in [23], should facilitate transition of this new paradigm of automatic multistage process control from a theoretical study into real-life industrial applications.

When it comes to challenges associated with data analytics for quality measurements considered in this paper, the main problem is understanding the relations between process parameters and quality characteristics in prismatic and non-prismatic parts, such as a turbine blade. Such models have not been developed yet and are dearly needed and are certain to be plagued by nonlinear dependencies and nonstationary noise characteristics. In addition, models relating process parameters to product quality characteristics can be utilized to feedback into the generation of measurement points so that those measurements can reflect the process characteristics and maximize controllability of the process, as suggested in [22]. Such considerations would greatly augment the purely functional approach to measurement generation described in our earlier publication [8].

## 3. Big Data Analytics in Cyber-Physical Manufacturing Metrology Model (CPM$^3$)

Figure 2 represents the concept of our Cyber-Physical Manufacturing Metrology Model (CPM$^3$) [8] that consists of the following elements: 1) Module for recognition of geometrical features (GF) from CAD/GD&T (Computer Aided Design/Geometrical Dimensioning and Tolerancing) model of the measurement part, 2) Intelligent inspection process planning (IIPP) module that generates inspection sequence, and 3) Module for measurement, analysis of the results, and generation of reports.

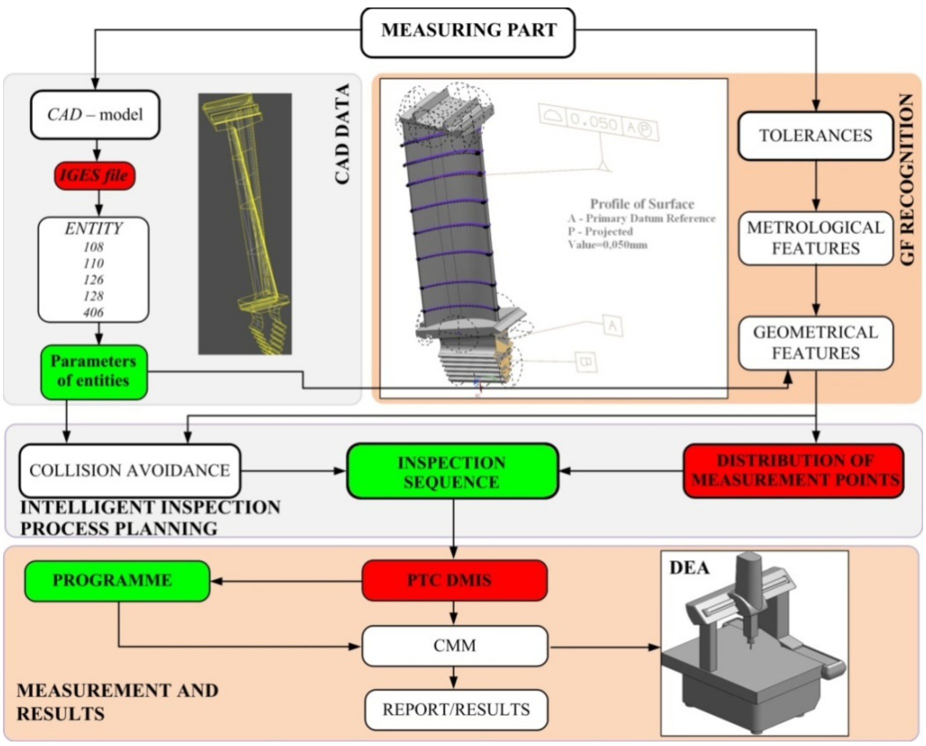



Fig. 2 Concept of Cyber-Physical Manufacturing Metrology Model (CPM$^3$)

All these modules are supported by data sets that transfer the information from outer world to the CPM$^3$, as well as between CPM$^3$ modules. Necessary CPM$^3$ data sets (marked red in Fig. 2) are: 1) Data set that represents the geometry of the inspection part in neutral format – in CPM[3] IGES (Initial Graphics Exchange Specification) is chosen; this data set is within GF recognition module; 2) set containing the distribution of measuring points – within IIPP module, and 3) PTC Creo DMIS data set within module for measurement. From CPM[3] point of view, these data sets represent big data sets that should be analyzed in order to extract relevant information for transfer from the preceding to the subsequent modules. Extracted information can be presented by optimal sets containing only unambiguous data necessary for the inspection at hand.

Thus, in each CPM[3] module corresponding sets should be processed in order to extract relevant information or to structure data. The elements of CPM[3] modules that are directly based on application of big data analytics (BDA) methods are marked green in Figure 2. They refer to the extraction of relevant GFs parameters from IGES file, to generation of inspection sequence by extraction and structuring measurement points and to generation of CMM program. BDA application in one module indirectly influences all other elements of CPM[3]. Namely, extraction of information from one of the given sets and its representation through the relevant set has significant influence on the results of all downstream processes.

### 3.1. Extraction of geometrical features from IGES

Although IGES data set is clearly structured, it has to be processed in order to extract relevant information regarding metrological features (MF). Namely, MFs consist of one or more GFs of interest, i.e. GFs that present surfaces that should be inspected. On the other hand, depending on the CAD system that generated IGES file and on the developer that created CAD model, IGES usually contains redundant data about certain surfaces and lines. In addition, it contains the data regarding the entire geometry of the measured part including GFs that do not correspond to MFs and that do not have to be inspected. Thus from IIPP point of view, IGES contains big data that need analysis in order extract the parameters that are relevant for the MFs.

An IGES file is composed of the following five sections: (1) start section, (2) global section, (3) directory entry section, (4) parameter data section, (5) terminate section. Geometric entities are defined in directory entry section and parameter data section and each entity is represented by certain code. The whole GF is presented through a set of structured entities. As an example, in Table 1 we provide a structure necessary for definition of surface of revolution (type 120), in this particular case cylinder, within IGES [24]. Similarly, other entities and GFs are defined. For example, rational B spline curve is represented by type 126 followed by spline parameters (knots, weights, control points).

To enable measurement path planning it is necessary to analyze IGES data set and to extract relevant information. Namely, from IGES data, we have to extract surface parameters - information that is suitable input for IIPP module. For some GFs this process requires the calculation of surface parameters - example of cylinder parameters is presented in Table 2, while for others, such as spline, they are directly extracted.

Table 1. IGES entities for definition of a cylinder

| Entity | Place in the line of IGES | | | |
|---|---|---|---|---|
| | 1 | 1 2 3 | 5 6 7 | 73-80 |
| Line (generatrix) | 110 | X1, Y1, Z1 (start point) | X2, Y2, Z2 (end point) | 4 - Seq. number |
| Line (axis) | 110 | X3, Y3, Z3 (start point) | X4, Y4, Z4 (end point) | 5 - Seq. number |
| Surface of revolution | 120 | seq. no. 1, seq. no. 2 | α1, α2 - start and end angle) | 3 - Seq. number |
| Direction | 123 | i1, j1, k1 (unit vector) | | 18 - Seq. number |
| Direction | 123 | i2, j2, k2 (unit vector) | | 28- Seq. number |

Table 2. Calculating cylinder's parameters

| Feature | Parameters |
|---|---|
| Diameter | $\mathrm{D} = \sqrt{(\mathrm{X}_2 - \mathrm{X}_1)^2 + (\mathrm{Y}_2 - \mathrm{Y}_1)^2 + (\mathrm{Z}_2 - \mathrm{Z}_1)^2}$ |
| Point on axis | $X_0 = X_1; Y_0 = Y_1; Z_0 = Z_1;$ |
| Height | $H = \sqrt{(X_4 - X_3)^2 + (Y_4 - Y_3)^2 + (Z_4 - Z_3)^2}$ |
| Axis direction | $\boldsymbol{n}\,[i_1\ j_1\ k_1]$ |

Figures 3a and 3b show examples of planar surface and cylinder parameters, which we will use to outline the process of MF parameters extraction. Each geometric feature is uniquely defined by the set of parameters with respect to the local coordinate system $OX_FY_FZ_F$ and the coordinate system of a measuring part $OX_WY_WZ_W$. These parameters could be: coordinates (X, Y, Z), diameter (D), height (H), width (a), length (b), vector of a primitive ($\boldsymbol{n}$), parameter of a fullness of a feature ($\boldsymbol{n_p}$). Vector $\boldsymbol{n}$ determines the orientation of primitive in a space. The position of a primitive is defined by the coordinates $X_0$, $Y_0$, $Z_0$. The parameter of fullness is defined by the unit vector of X-axis of a feature: the value of a parameter $\boldsymbol{n_p}$=1 implies a full feature and the value $\boldsymbol{n_p}$=-1 implies an empty feature. The parameter of fullness and the vector of a feature will define the direction of a measuring probe access during the planning and simulation measurement path (Figures 3c and 3d).

### 3.2. Distribution of measurement points and path planning

Measuring points set and inspection path are generated from parametric representation of MFs. CPM[3] has different strategies for distribution of measurement points in regular (planar and quadric surfaces) and free form surfaces. In regular surfaces, CPM[3] generates a set of measurement points using modified Hemmersley sequences [25, 26]. As an example, by this approach, $N$ measurement points $\mathbf{P_i}(x_i, y_i, z_i)$ on cylinder are generated using the relations (1) where $R$ represent the radius, and $h$ the height of cylinder. Examples of generated measurement points for planar surface and cylinder are presented in Figures 3c and 3d. Nevertheless obtained set of measurement points contains large amount of data that is not appropriately structured. Further analysis of this data is necessary in order to obtain collision free measurement path during motion of measurement probe from one GF to the other within the same MF.

From measurement points set we extract optimal collision free measurement path (Figure 3e) using ant colony optimization algorithm. Details regarding generation and optimization of measuring path are given in [25, 26].

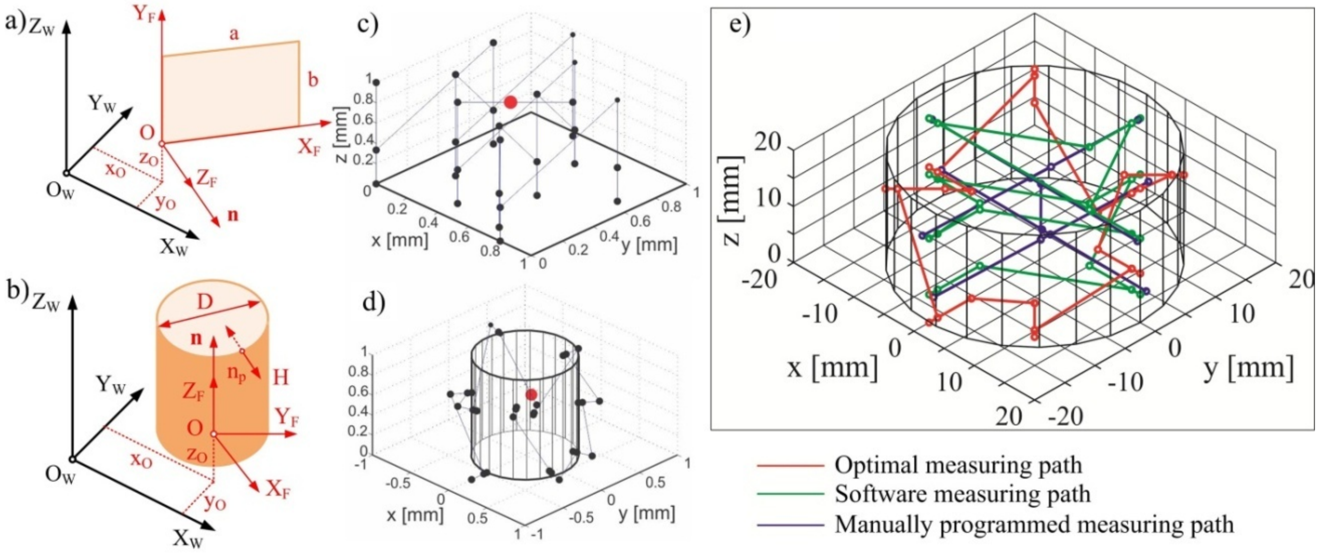
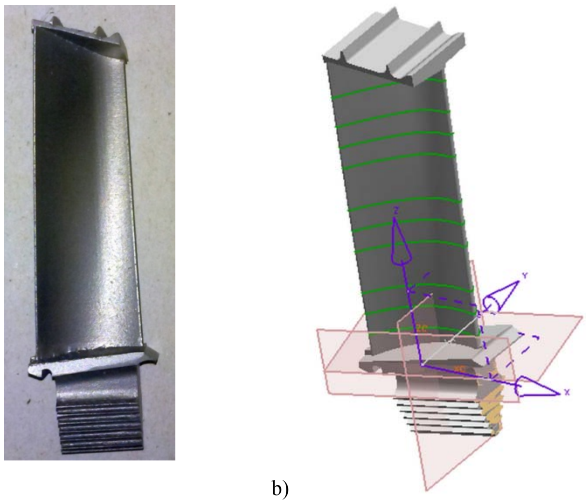



Figure 3. Extraction of GF and generation of measuring path for parametric surfaces



a) b)

Figure 4. a) a photo of turbine blade manufactured using additive manufacturing technology - Selective Laser Sintering; b) extracted control sections and points

$$x_i = R\cos\left(-\frac{\pi}{2} - \frac{2\pi}{N} i\right)$$
$$y_i = R\sin\left(-\frac{\pi}{2} - \frac{2\pi}{N} i\right)$$
$$z_i = \left(\sum_{j=0}^{i-1}\left(\frac{i}{2^j} \bmod 2\right)2^{-(j+1)}\right)h \qquad (1)$$

For free form surfaces alternative approach for measurement points set generation is employed. In this kind of surfaces, it is necessary to define the number of control sections and number and distribution of measurement points in each section.

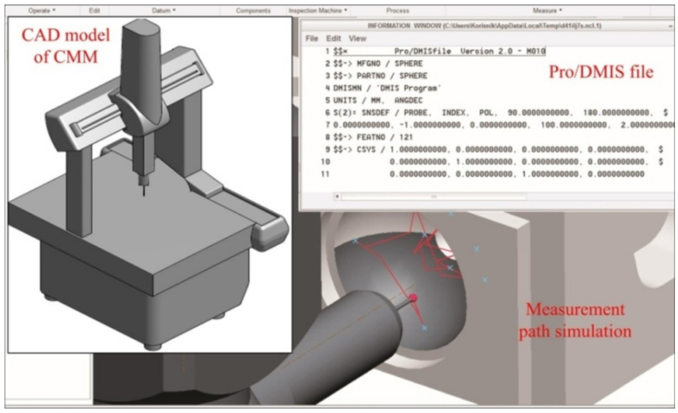



Figure 5. Generation of Pro/DMIS file and simulation of measurement path.

According to the findings from [27] we have selected uniform distribution of measurement points. In addition, it has been shown [27] that there is a non-linear (quadratic) functional correlation, expressed through regression relations between measurement error on one hand and number of control sections and measurement points in each section of the free form surface on the other.

An example of measuring points set for turbine blade (free form surface) is presented in Figure 4. Details of algorithm for generation of collision free measurement path from measurement points are given in [8].

### 3.3. Generation of PTC Creo DMIS file

Inspection sequence obtained from IIPP module is in the point-to-point form, and it does not represent suitable input for CMM. However, this form can be readily imported in CAD/CAM software. In CPM[3] we opted to use CMM module of PTC Creo. After importing the points on the inspection sequence into this module, the CMM path can be simulated

(Fig. 5). PTC Creo translates point-to point path into Pro/DMIS (.ncl) format that is transferred into control data list for selected CMM by selecting the appropriate post-processor.

## 4. Conclusion

During generation of $CPM^3$ framework we have faced a number of issues referring to the big data analysis, i.e. extraction of useful information from data sets, and finding the relevant structure from unstructured data sets. The first problem represented the extraction of GFs' parameters from neutral CAD format. We solved this problem by generation of the base of rules containing analysis approaches for each particular GF type and its parameters.

More complex problem was the structuring of measurement points obtained from GFs and generation of optimal measurement path. In regular surfaces, measurement points were selected using Hemmersley sequences, while extraction of optimal measurement points from free form surfaces required more sophisticated approach. In free form surfaces regression analysis using ANOVA was employed to obtain the number of control sections and measurement points. Nevertheless, in both cases obtained measurement points set was unstructured and inconvenient for generation of measurement path. To generate optimal measurement path, we had to find the spatial structure of points in the set using ant colony optimization.

Our future work will consider the development of $CPM^3$ modules that would enable the generation of virtual models of the parts using measurement results and their connection to the downstream and upstream processes in CPMS.

## Acknowledgements

This research was partially supported by Serbian Ministry of Education, Science and Technological Development under research grants TR35022 and TR35020.

## References

[1] Monostori L, Kádár B, Bauernhansl T, Kondoh S, Kumara S, Reinhart G, Sauer O, Schuh G, Sihn W, Ueda K. Cyber-physical systems in manufacturing. CIRP Annals - Manufacturing Technology, 2016; 65:621–641.
[2] VDI/VDE-Gesellschaft Mess- und Automatisierungstechnik (2015) Reference Architecture Model Industrie 4.0 (RAMI4.0). http://www.zvei.org/Downloads/Automation/5305%20Publikation%20GMA%20Status%20Report%20ZVEI%20Reference%20Architecture%20Model.pdf Accessed 14 Feb 2017
[3] Lee J, Bagheri B, Kao HA. A Cyber-Physical Systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 2015;3:18-25.
[4] Lee J, Kao HA, Yang S. Service innovation and smart analytics for Industry 4.0 and big data environment. The 6th CIRP Conference on Industrial Product-Service Systems, Procedia CIRP, 2014;16:3-8.
[5] Lee J, Ardakani HD, Yang H, Bagheri B. Industrial big data analytics and cyber-physical systems for future maintenance & service innovation. The Fourth International Conference on Through-life Engineering Services, Procedia CIRP, 2015;38:3-7.
[6] Schmitt R, Dietrich F, Dröder K. Big Data Methods for Precision Assembly. 6th CIRP Conference on Assembly Technologies and Systems (CATS), Procedia CIRP, 2016;44:91-96.
[7] Babiceanu RF, Seker R. Big Data and virtualization for manufacturing cyber-physical systems: A survey of the current status and future outlook. Computers in Industry, 2016;81:128-137.
[8] Majstorovic V, Stojadinovic S, Zivkovic S, Djurdjanovic D, Jakovljevic Z, Gligorijevic N. Cyber-Physical Manufacturing Metrology Model ($CPM^3$) for Sculptured Surfaces – Turbine Blade Application. The 50th CIRP Conference on Manufacturing Systems, Procedia CIRP, 2017;63:658-663.
[9] Hu SJ. Stream of Variation Theory for Automotive Body Assembly. Annals of CIRP - Manufacturing Technology, 1997;46(1):1-6.
[10] Huang Q, Zhou S, Shi J.Diagnosis of Multi-Operational Machining Processes by Using Virtual Machining. Robotics and Computer Integrated Manufacturing, 2002;18:233-239.
[11] Ceglarek D, Shi J.Fixture Failure Diagnosis for Autobody Assembly Using Pattern Recognition. ASME Transactions, Journal of Engineering for Industry, 1996;118:55-65.
[12] Ceglarek D, Shi J.Fixture Failure Diagnosis for Sheet Metal Assembly with Consideration of Measurement Noise. ASME Transactions, Journal of Manufacturing Science and Engineering, 1996;121:771-777.
[13] Ding Y, Ceglarek D, ShiJ. Fault Diagnosis of Multistage Manufacturing Processes by Using State Space Approach. ASME Transactions, Journal of Manufacturing Science and Engineering, 2002;124:313-322.
[14] Huang Q,Zhou S, Shi J.Diagnosis of Multi-Operational Machining Processes by Using Virtual Machining. Robotics and Computer Integrated Manufacturing, 2002;18:233-239.
[15] Zhou S, Chen Y, ShiJ. Root Cause Estimation and Statistical Testing for Quality Improvement of Multistage Manufacturing Processes. IEEE Transactions on Automation Science and Engineering, 2003;1:73-83.
[16] Jin J, Shi J.State Space Modeling of Sheet Metal Assembly for Dimensional Control. ASME Journal of Manufacturing Science and Engineering, 1999;121(4):756-762.
[17] Zhou S, Huang Q, Shi J. State Space Modeling of Dimensional Variation Propagation in Multistage Machining Process. IEEE Transactions on Robotics and Automation, 2003;19(2):296-309.
[18] Camelio J, Hu JS, Ceglarek D. Modeling and Control of Compliant Assembly Systems. Annals of CIRP – Manufacturing Technology, 2006;55(1):19-22.
[19] Djurdjanovic D, Zhu J. Stream of Variation Model Based Compensation of. Dimensional Errors in Multistage Manufacturing. In: Proceedings of the 2005 ASME International Mechanical Engineering Congress and Exposition, 2005.
[20] Jiao Y, Djurdjanovic D. Joint Allocation of Measurement Points and Controllable Tooling Machines in Multistage Manufacturing Processes. Transactions of IIE, 2010;42(10):703-720.
[21] Jin R, Shi J. Reconfigured Piecewise Regression for Multistage Process Control. Transactions of IIE, 2012;44(4):249-261.
[22] Jiao Y, Djurdjanovic D. Stochastic Control of Multilayer Overlay in Lithography Processes. IEEE Transactions on Semiconductor Manufacturing, 2011;24(3):404-417.
[23] Djurdjanovic D, Jiao Y, Majstorovic V.Multistage Manufacturing Process Control Robust to Inaccurate Knowledge about Process Noise. CIRP Annals, 2017;66(1).
[24] IGES/PDESOrganization, InitialGraphicsExchangeSpecification: IGES 5.3, N. Charleston, SC: U.S. ProductDataAssociation, 1996.
[25] Stojadinovic S, Majstorovic V, Durakbasa N, Sibalija T. Towards an intelligent approach for CMM inspection planning of prismatic parts. Measurement, 2016;92:326–339.
[26] Stojadinovic, S., Majstorovic, V., Durakbasa, N., Sibalija, T. Ants Colony Optimization of the Measuring Path of Prismatic Parts on a CMM. Metrology and Measurement Systems, 2016;23(1):119-132.
[27] Sibalija T, Zivkovic S, Fountas N, Majstorovic V, Macuzic J, Vaxevanidis N. Virtual Optimisation of CAI Process Parameters for the Sculptured Surface Inspection. Procedia CIRP, 2016;57:574-579.