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Process control in CNC manufacturing for discrete components: A STEP-NC compliant framework

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Abstract

With today's highly competitive global manufacturing marketplace, the pressure for right-first-time manufacture has never been so high. New emerging data standards combined with machine data collection methods, such as in-process verification lead the way to a complete paradigm shift from the traditional manufacturing and inspection to intelligent networked process control. Low-level G and M codes offer very limited information on machine capabilities or work piece characteristics which consequently, results in no information being available on manufacturing processes, inspection plans and work piece attributes in terms of tolerances, etc. and design features to computer numerically controlled (CNC) machines. One solution to the aforementioned problems is using STEP-NC (ISO 14649) suite of standards, which aim to provide higher-level information for process control. In this paper, the authors provide a definition for process control in CNC manufacturing and identify the challenges in achieving process control in current CNC manufacturing scenario. The paper then introduces a STEP-compliant framework that makes use of self-learning algorithms that enable the manufacturing system to learn from previous data and results in eliminating the errors and consistently producing quality products. The framework relies on knowledge discovery methods such as data mining encapsulated in a process analyser to derive rules for corrective measures to control the manufacturing process. The design for the knowledge-based process analyser and the various process control mechanisms conclude the paper.

Keywords: STEP-NC; Process control; CNC

1. Introduction

In modern manufacturing scenarios, the complex nature of industrial processes, the demand for quality products at ever reducing lead times and the strive for attaining higher profitability is enforcing researchers as well as practitioners to attain improved process control of the computer numerically controlled (CNC) manufacturing system.

The complex nature of the different manufacturing processes, their analysis and control has always presented a challenge for the researchers as well as practitioners. Process control has evolved as a term from a number of different industries such as chemical process industries, semiconductor-manufacturing industries and machining industries and thus various researchers have presented a wide range of perspectives regarding this area. In CNC machining, with the existence of complex processes that start from the design of a part to its manufacture, process control is an integral part of the chain.

The pursuit for automated manufacturing process control started in 1950s with the introduction of numerical control (NC) machines. These machines had their controller coded in their electronic circuitry and the punch tapes were the only means for loading the part programmes onto the controllers. The first numerically controlled machine tool was a three-axis milling machine developed in 1952 at the Servomechanisms laboratory at the Massachusetts Institute of Technology, USA. The continuous development of computer technologies proved beneficiary and the first

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CNC machine was developed in late 1960s where the hardwired logic of previous controllers got replaced by an onboard computer.

One of the major drawbacks of traditional CNC manufacturing is the reliance over the experience and knowledge of the operator to readjust the process parameters based on his observations manually. The result is the selection of process parameters by the operators based on local historical knowledge and dated machining handbooks. This bespoke approach reduces the repeatability and the effectiveness of a manufacturing company in realising full production potential.

In addition to process parameters, variables such as tool wear, thermal changes, dimensional inaccuracies and other disturbances affect the manufactured products. These variables are dependent on manufacturing processes, inspection planning and work piece characteristics, which emphasise the need for process control in CNC manufacturing that relies on optimisation and control of the machining process.

In this regard, there is a major requirement to seek standardised methods for representation of product and process modelling information across the manufacturing life cycle. Product models are well established commercially at the design phase with information relating to geometry, tolerances, functional capability, assemblies etc. already defined in current standards such as STEP (ISO 10303[1]) and represented within CAD systems; Significant effort is now being placed on developing effective product modelling strategies for supporting process planning and CNC manufacture.

STEP-NC offers the opportunity to effectively maintain high level and standardised information from the design phase to a new breed of intelligent STEP-compliant CNC controller. This facilitates bi-directional information exchange with the diverse software CAx systems (e.g. CAD/CAPP/CAM[1]) in accordance with the manufacturing processes.

This paper outlines an intelligent process control system for CNC manufacturing based on a STEP-NC-oriented knowledge-based framework. The key contributions of the paper are the identification of the process control elements, STEP-NC compliant framework for process control and a working outline of self-learning algorithms within a knowledge-based process analyser.

The first part of the paper provides a brief literature review of the process control techniques together with an outline of the state of the art in CNC manufacturing. It is followed by the definition of the process control and identification of its key elements. The framework for STEP-compliant process control is then outlined and discussed together with the knowledge-based process analyser. The paper concludes with the discussion of the application of the knowledge-based tools in providing the corrective measures for processing parameters.

2. Process control in manufacturing

Process control in the modern manufacturing scenario has been mainly dependent on the developments in machine tools and their controllers. These developments in machine tool axis movements, acceleration of the spindles as well as axes, position and velocity are controlled by servomechanism control loops, machining process monitoring and control are briefly reviewed below.

Research [2,3] has already been carried out in different types of machine process monitoring and control techniques. This includes the development of the on-line sensors, which use acoustics, optical, electrical, thermal and magnetic sensing systems. These sensors help in direct observation of the process variables or assist in judgement based on indirect measurements. These process-monitoring techniques are mainly aimed at estimating various machining process variables especially tool condition monitoring, predicting wear, surface roughness and chatter detection.

The quality of the machined parts is directly affected by the accuracy and precision of CNC machine tools. This emphasises the need to investigate the machine tool capability in terms of repeatability and accuracy along with the manufacturing errors that can be eliminated and lead towards the production of quality parts regularly. In the past, researchers [4] have identified the machine tool errors that affect the performance of the machine tool control and the quality of the product. A detailed study of the operating parameters and the machining errors in the broad domain of manufacturing processes are carried out by Brecher et al. [5] Drozda and Wick [6] and Gillespie [7]. Yandayan and Burdekin [8] also categorised machine tool errors into two classes' i.e. random errors and stochastic errors.

These errors [8] have been further classified into geometric error, static/loading, thermal effects, machine tool vibration, chatter, spindle vibration, spindle deflection and control error. Various studies have been conducted to investigate these errors and their compensation during machining process. These approaches include fuzzy-based techniques, neural networks, genetic algorithms, FEM-based techniques [9,10], etc.

The machining forces [11,12] also play a vital role in increasing the operation productivity, minimising the tool breakage, managing the tool deflections that control the machining errors and improving the part quality. Since adequate regulation of the machining force is a challenging task, a number of adaptive techniques have been investigated by the researchers. These adaptive controllers [13] eliminate the requirement of the off-line calibration by evaluating the force process model parameters on-line. These systems exhibit quite a complex behaviour, which is difficult to develop, analyse, implement, and maintain and

[1]CAD/CAPP/CAM represents Computer Aided Design, Computer Aided Process Planning and Compute Aided Manufacturing.

thus have not been favourable with the industry for practical applications.

It is commonly required for a machining system to track a certain contour without violating prescribed error limits. Measuring tool and axis velocities is not as accurate as measuring their positions. The design for adaptive control systems within any machine tool control architecture [14] falls into one of the following categories:

(I) centralised control,
(II) decentralised control,
(III) hierarchical control.

Estimation of machining forces and control over these forces plays a big role in achieving process control. The conventional controller having a fixed gain, fail to maintain the system performance with dynamic force changes during machining. In this regard, adaptive controllers have proved to be successful in estimating force model parameters on-line and adjusting the controller gain [15].

Adaptive control systems primarily strive to achieve the following two objectives:

I. estimation of machining process parameters on-line,
II. utilisation of estimated parameters in calculating controller gain for effectively achieving process control in machining operations.

Process control in machining has been traditionally classified into categories as: adaptive control with constraints (ACC), adaptive control with optimisation (ACO) and geometric adaptive controller (GAC). ACC systems are mainly aimed towards adjusting process variable such as force or power in real time relative to appropriate machining conditions to reduce machining costs and increase machine tool efficiency. These systems are capable of maintaining maximum working conditions in an evolving machining process [16]. Ulsoy and Koren [17] have defined the objective of ACC systems as appropriate feed rate tuning for controlling the cutting force, which is the maximum cutting force relative to threshold tool breakage conditions. ACO systems [18] have also been developed to gain the control over the machining process parameters such as feedrate, spindle speed or depth of cut for maximising the process response for attaining better quality products. The primary objective of the GAC systems is to maximise the quality of the products in terms of finishing operations [19]. GAC systems take structural deflection and tool wear as machining constraints for optimising the finishing quality.

In recent years, researchers [20,21] have also made an attempt towards achieving the high precision contour machining and in this regard developed more accurate CNC systems. Rule-based controllers are developed that can improve the contouring accuracy in the awake of machining errors such as friction. It has been also identified that contouring performance of CNC feed drive systems can be improved by taking the dynamics of the axes into account while planning the trajectories of each axis.

The statistical quality control techniques [22] also play an important role in controlling the machining processes. These quality control techniques based on the different control charts are capable of identifying uncertain states of machining process in advance.

It has been established that different machine tools display different stiffness, damping and frequency characteristics [23]. This emphasises the need for having confidence in the machine for machining parts in tolerance limit consistently, as well as, measuring them. Till now, part dimensional accuracy and inspection has largely been carried out on CMMs, which is widely recognised as being consistent for estimating [24] the appropriateness of the machined parts. In recent years, on-machine measurement using touch trigger probes mounted on spindle in machine tool has been recognised as vital for achieving the process control [25] in CNC manufacturing. It is realised that by using a CNC machine tool also as measuring equipment [26], closed-loop process control can be achieved in terms of automatic tool offsets for avoiding machining defects. In this regard, recent research has been concentrated on investigating the capabilities of on-machine measurement conforming to the machine tool's capability.

Another important aspect in machining automation that affects the quality of the parts is preventive maintenance techniques [27]. In recent years, a relationship has been formulated between the equipment maintenance and product quality using the quality control techniques.

Knowledge-based techniques have been applied in various domains of the manufacturing such as prediction and optimisation of machining parameters [28]. These techniques play an important role in manufacturing data analysis. The various applications of these tools have also been reported and can be useful in realising the process control.

3. State-of-the-art in CNC manufacturing

The present CNC manufacturing process control loop has remained unchanged for more than 20 years [29]. Today's PC-CNC controllers are still only utilised for low level tool path NC code execution, with no access to high-level information on the major activities of machine set-up, tooling set-up/management, inspection planning or results feedback. Any error in the final manufactured part cannot be identified or traced back to its source. This is depicted in Fig. 1, which illustrates the feedback in a system that cannot modify the process parameters in CAPP/CAM and manufacturing resources to manufacture the parts consistently.

Product models are widely used for representing design and manufacture of the components. There are ranges of information standards (ISO-10303-STEP) to represent a product model, but it is recognised that features are vital entities to represent such geometry and their planning and

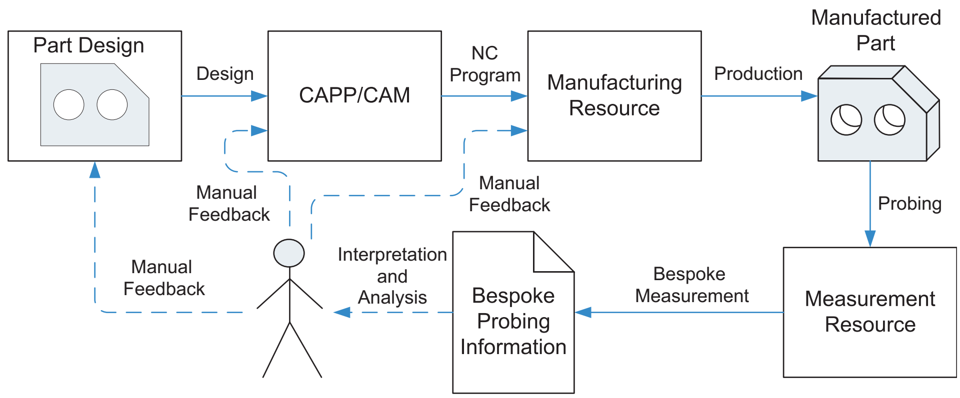

Fig. 1. Current process control loop in the CNC manufacturing.

manufacturing information. Even where product models can use features to represent the part design, part-manufacturing data are generated by CAM systems, specific to an individual machine tool, with vendor-specific interpretation of toolpath commands as well as on-machine inspection instructions. The existing inspection standards for programming and for analysis (i.e. dimensional measuring interface standard (DMIS) [30]) are implemented on vendor-specific hardware and can only be utilised for CMMs. The present system therefore, lacks a standardised form of feedback that can be analysed to provide the corrective measures so that process variations can be evaluated and subsequently compensated.

In order to provide the standardised structured feedback for process control, the following points need to be considered:

I. The generic format of the interpreted results data and also the required semantics that can be analysed and fed back into the system need to be defined.
II. The different standards conforming to the inspection of a component, fixturing for the part on the machine tool and tooling requirements need to be investigated so that inspection can be achieved in a strategic and standardised manner.
III. The acquisition of the know-how pertaining to the machining process parameters will need to be represented in a formalised manner within the knowledge base.
IV. The different types of the manufacturing errors need to be analysed and classified.
V. The types of feedback need to be decided so that feedback related to the local machining and global manufacturing can be realised and consequently fed back appropriately.
VI. The different knowledge-based tools are to be analysed to effectively provide the feedback from the past experience data set of the component in to the manufacturing system.

4. Various types of process control in CNC manufacturing

Process control in CNC manufacturing is defined by the authors as the ability to monitor machining parameters and apply corrective measures where appropriate in order to provide confidence in the machine tools to consistently produce parts within desired tolerance limits.

The authors have identified three types of process control relevant to CNC manufacturing: static errors, dimensional errors and surface roughness errors. A fish bone diagram for process control in CNC manufacturing is shown in Fig. 2 and represents the authors view of classifying process control into three types. The first type of process control feedback compensates for the inherent inaccuracies in the machine tool. Tool offsets and compensation for dimensional inaccuracy are compensated as the second type of feedback. The third type is related with the feedback of process parameters for better surface roughness.

5. STEP-NC compliant process control framework

STEP-NC is a data model which represents an intelligent CNC control and is formally known as the standard ISO 14649. Contrary to the current NC programming standard (ISO 6983) [31], ISO 14649 is not a method for part programming and does not normally describe the tool movements for a CNC machine. Instead, ISO 14649 provides a hierarchical data model for CNCs with a detailed and structured data interface that incorporates feature-based programming where there is a range of information such as the feature to be machined, tool types used, the operations to perform and the work plan.

Though it is possible to closely define the machine tool trajectory using STEP-NC, the aim of the standard is to allow these decisions to be made by a new breed of intelligent controller. It is the aim that STEP-NC part programmes may be written once and used on many different types of machine tool controller providing the machine has the required process capabilities. One critical

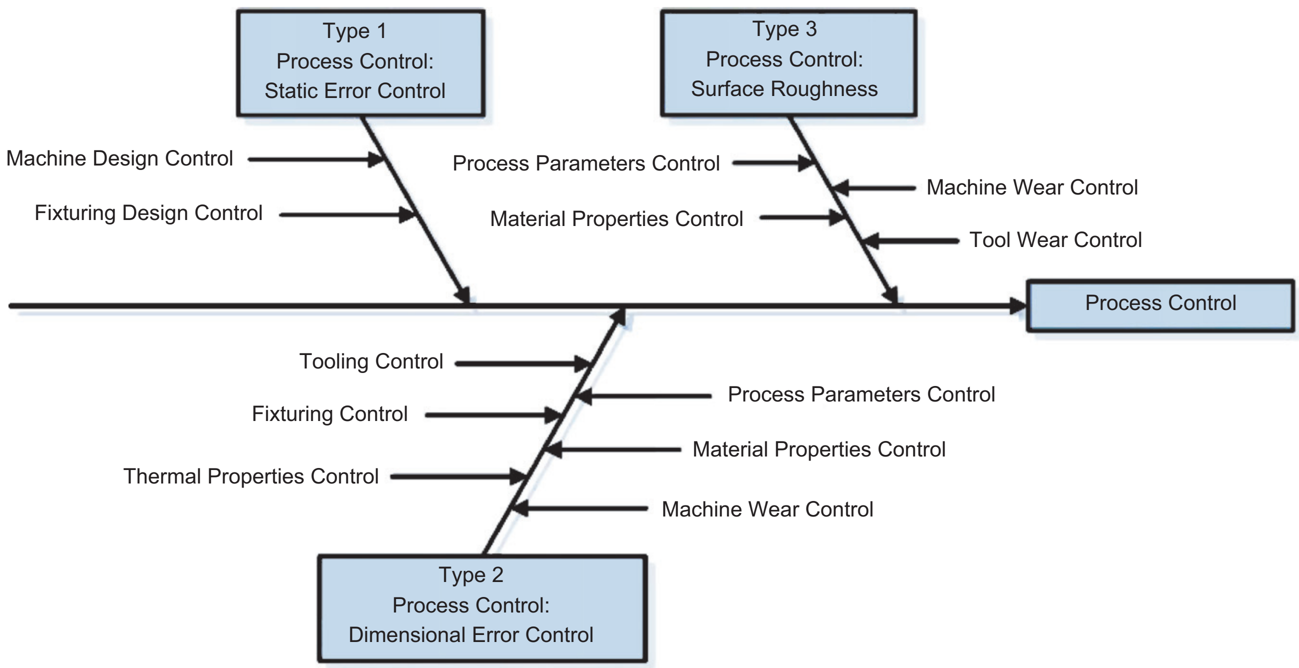

Fig. 2. Process control elements in CNC manufacturing.

issue is that the toolpath and inspection probe path movements information is optional and should ideally be generated at the machine by the CNC controller. In addition, the standard also includes the data model for feedback of inspection results within the updated STEP-NC file for the manufactured part, which could then be analysed.

Geometric information is defined by features (as in AP224 [32]) with machining and inspection operations known as working steps performed on one or more features. These working steps provide the basis of a work plan to manufacture the component. One important point should be recognised, is that this code is the STEP-NC transfer (physical) file, which is imported/exported into and out of a STEP-NC intelligent controller. This file would be interpreted by the controller, enabling CNC operators to interact at a working step (i.e. machining operation) level via an intelligent MDI or CAD/CAM system at the controller. It is worth noting that currently two versions of STEP-NC are being developed by ISO. The first is the application reference model (ARM) version of ISO14649 (i.e. ISO14649) and the other is the Application Interpreted Model (AIM) version of ISO14649 (i.e. AP238 [33]).

A STEP-compliant process control framework based on STEP-NC for closing the CAM to CNC feedback loop has been proposed by the authors in this paper. STEP-NC is seen by the authors as a valuable enabler for process control as it provides CNC control with geometric and process planning data in a consistent format. In addition, these data which can be updated based on process control feedback introduces the possibility of greater standardisation in process control for CNC machining. A view of this STEP-NC compliant process control framework is presented in Fig. 3 illustrating its major functional elements.

STEP-compliant information is used at heart of the framework and defines the specifications for the part and its features according to the available standards. This standardised information for the process control defines, the part and feature definition and tolerance definition in conformance to AP 203, AP 240, AP 224, AP 219, ISO-14649 Part-10 [34–37]. The identified inspection features are defined for the part as entities in ISO-14649 part-16 [38] which also enables these features to be linked with tolerances. These STEP data represent the opportunity to provide an overall data repository for both design and manufacturing information recognised as a product data model.

The functionalities of the various elements shown in the framework are as follows:

5.1. *Design interpreter*

This interprets the part design specifications or features on the basis of which the manufacturing operations of the part are to be carried out. This interprets AP 203 data into AP 224 in the form of manufacturing features, which is used by a feature-based CAPP/CAM system for the manufacturing of the part. A number of feature recognition systems are available and one such system is outlined by Suh and Cheon [39].

5.2. *Feature-based CAPP/CAM system*

This phase carries out the process planning based on the manufacturing features defined in AP 224. This also

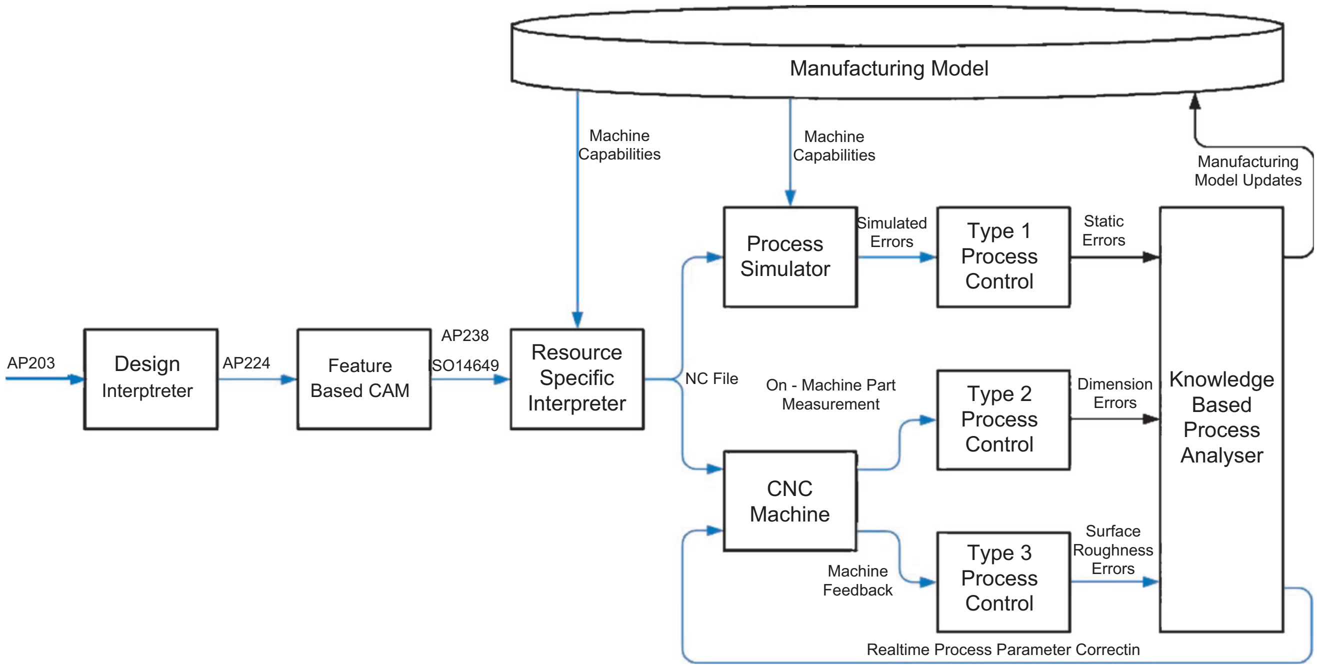

Fig. 3. STEP-NC compliant process control framework.

contains tooling, fixturing and machine model information needed for the manufacturing of the component. A STEP-NC compliant file (i.e. ISO14649) is generated that contains the machining and measurement work plan, working steps, entities, strategies for manufacturing and inspection of the part.

5.3. Resource-specific interpreter

This interpreter generates STEP-NC like part tooling information, part fixturing information, part manufacturing information and measurement code for the component. A NC part programme is created for the manufacture of the part. This interpreter encompasses the available resource conditions and is linked with the manufacturing model, which provides specific machine resource elements.

5.4. Manufacturing model

The manufacturing model represents the process control information in CNC and includes machine model and process capability model. The primary objective of the manufacturing model is to map the resources in the machine tool for process control activities. The machine resource elements represent the information related to materials, machine tools, cutting tools and assemblies, fixtures, jigs, control devices and the communication equipment. The machine resource model for process control is being developed on the basis of standards such as AP 240, AP 219, ISO-14649 part10, 11, 16 [40]. The major elements for the resource model have been identified as fixturing, assembly, cutting component attributes, tool assembly class, inspection process information, surface roughness, machine class and controller class. The process capability model maps the manufacturing ability of the machine tool in carrying out the process control experiments. This model is aimed to develop a rule-based reasoning which act as constraints for given operations. In an initial view towards realisation of the framework, surface roughness (for machining quality of surface), measuring accuracy, tool wear in terms of tool life, repeatability and circularity are recognised as elements of process capability model. The process control simulator feeds back the compensation for the fixturing and thermal errors to the manufacturing model and the knowledge-based analyser feeds back the corrective measures for the process deviation for the production and set up data for better surface texture of the part.

5.5. Process control

The three types of process control previously identified in Section 4 have been utilised in the framework, namely simulated process control, product control and machine control.

Type 1 process control: This first type is termed as simulated process control, and is related to the compensation of static errors i.e. fixturing and thermal errors which are identified as a major source of errors [41] to the manufacturing model and feature-based CAPP/CAM. This operation is to be carried out before the machining of the part so that geometrical inaccuracies of the machine tool can be compensated as the machine tool inaccuracies have a major impact over the final quality. These types of errors are the major source of errors in the machine tool. The important source of thermal errors are identified [41] as heat generated by the machine tool and cutting forces during the machining of the part. Fixture set-up, clamping forces, contact surface between workpiece and fixture and deformation of the lift-off of workpiece are major sources of fixturing errors. The laser interferometer is typically used for machine tool accuracy testing for static errors. The fixturing set-up, contact surface between workpiece and fixture, testing instrument and thermal expansions are modelled in the manufacturing model and used by this process control simulator. Thermal profiles and fixturing forces are to be modelled. This process control simulator makes also use of knowledge-based tools such as neural networks to provide the corrective measure for compensating the static inaccuracies of machine.

Type 2 process control: The second type of feedback is identified for compensating the dimensional inaccuracies in terms of tolerances or tool offsets in the product information. This feedback is related to on-machine measurement which is recognised as an important element for achieving process control where spindle inspection probes are to be used for carrying out in-process inspection. The inspection entities for the part are defined in ISO-14649 part-16 and AP219 which is also modelled within the STEP information chain. The probing sequences and working steps to carry out the measurement are modelled in the manufacturing model. The inspection results are analysed by the knowledge-based analyser and tool offsets are fed back for compensating the tool wear to the manufacturing model and product model.

Type 3 process control: The third type of process control is aimed to feedback the process parameters for the better surface finish of the part. Parts quality is also dependent on the surface roughness which is measured using dynamometers. Machined surface condition is also modelled in the process capability model of the manufacturing model. The dynamometer provides the spindle forces which becomes the basis for calculating the roughness. The knowledge-based process analyser evaluates the different surface roughness values for various process parameters and provides the appropriate process parameters for better surface roughness and minimum tool wear. This is then fed back to the manufacturing and updated product information in the framework.

5.6. Knowledge-based process analyser

The knowledge-based process analyser investigates the pattern of process variations from the obtained data set that relates to the process deviations for the particular component for a set of experiments. This knowledge-based analyser uses knowledge-based tools to obtain a certain pattern of process variation for the part that can be fed back for the corrective measures.

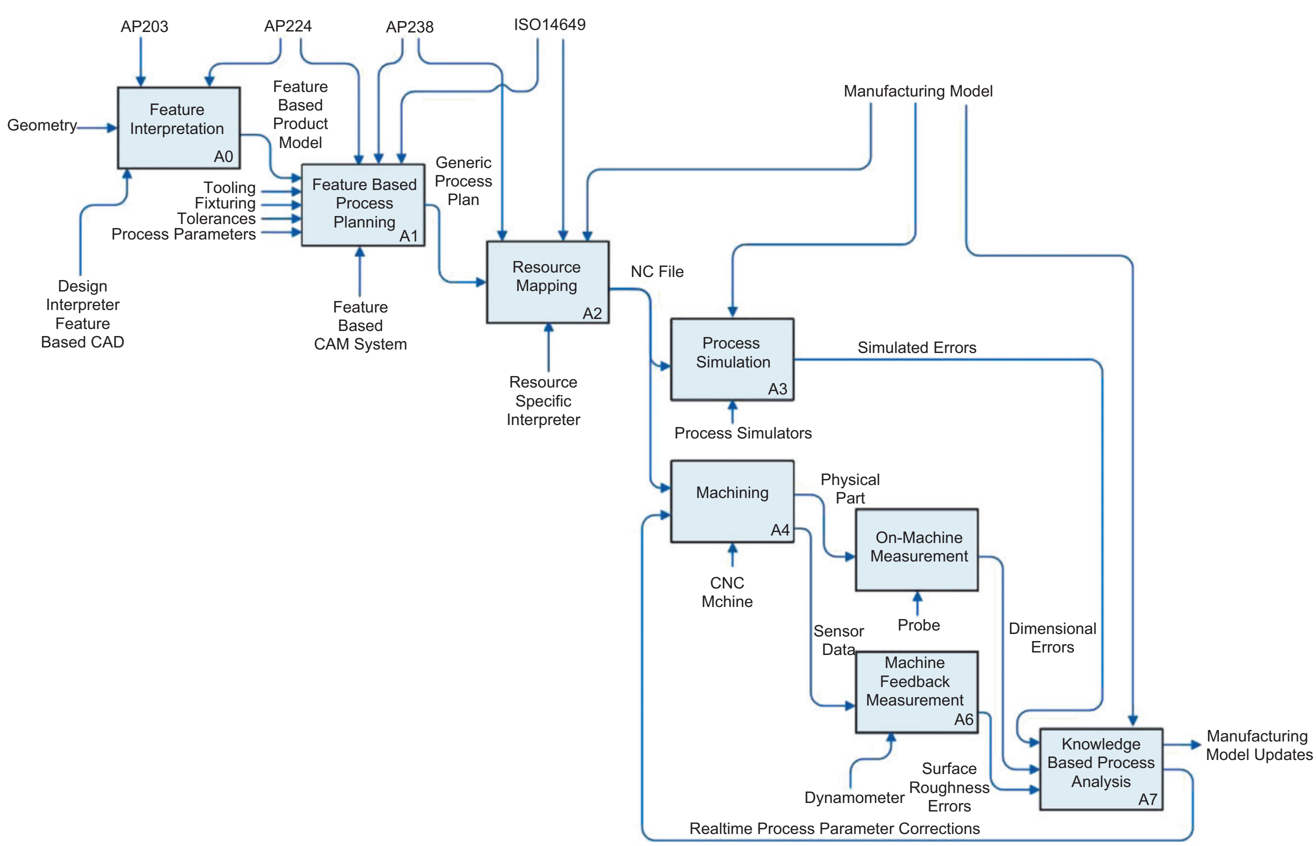

Fig. 4. IDEF0 representation of STEP-compliant process control framework.

An IDEF0 representation of information transfer within the framework is illustrated in Fig. 4.

6. Functional framework for the knowledge-based process analyser

The role of the knowledge in the CNC manufacturing process control is to explore the feedback of the process parameters from the CNC to the CAM system. The authors have classified the knowledge requirements into four categories i.e. knowledge acquisition, updating knowledge base, knowledge representation and knowledge reproduction and utilisation. The functionalities of these elements of the knowledge-based process control system are briefly presented as follows:

I. *Knowledge acquisition*: To build a knowledge base on the basis of the results obtained from a set of experiments for various process parameters. The knowledge base is built by analysing the STEP-NC file related to manufacturing information and process parameters for the part.
II. *Updating knowledge base*: Mobile agents are used to support the continuous update of the database, which helps in keeping a record of the previous parameters and subsequently analysing it.
III. *Knowledge representation*: This is used to represent the knowledge pertaining to features and different process control parameters. Different clustering techniques that cluster different parameters based on their similarity attribute are also to be used for representing the knowledge in the structured form.
IV. *Knowledge reproduction and utilisation*: Different knowledge-based tools, and data mining techniques such as rough set theory are to be applied to provide the corrective measures for the process parameters from the available knowledge base. The pattern obtained for the different process parameters are to subsequently fed back to be able to produce the products with least deviations of the required parameters for the part.

6.1. *Working principal of knowledge-based process analyser*

Self-learning algorithms such as data mining techniques [42] are used to identify the potential patterns in the process parameters that control the manufacturing process. Knowledge is extracted from a large number of experimental data items for the machining operation, which are expressed in the form of decision rules to take corrective measures for deviation in process parameters. The operational structure of the knowledge-based process analyser is shown in Fig. 5.

The different functionalities of this knowledge-based analyser are as follows:

(1) *Knowledge acquisition*: This phase builds a knowledge base on the basis of results obtained from a set of experiments pertaining to various process parameters. This is based on the results obtained from the comparative analyser which analyses the results interpreted by the interpreter from the machine. These are based on the comparison of the obtained process parameters with the desired parameters. This helps in generating a data set of the input process parameters with their effect on those parameters that control the quality of the obtained products.
(2) *Data set generation*: Based on the knowledge acquisition of the various process results pertaining to various machining processes, a data set is generated that is analysed by the knowledge-based tools. A comprehensive data set is generated which contains the result of experiments conducted over the desired part type. A structured form of data set for the analysis of the process parameters is shown in (Table 1).
(3) *Knowledge analysis*: Knowledge-based tools such as rough set theory is employed to extract the knowledge from the data sets. Rough set theory is used to classify the imprecise, uncertain or knowledge expressed in terms of data acquired from experience or historical facts. It helps in extracting rules from an available data set and determines the data regularities. The advantage of applying rough set theory for the analysis lies in the fact that it does not need any preliminary or additional information such as its probabilistic or membership values about the data set. This approach is used to reduce the size of the data set and removes the inconsistent data, which helps in establishing the dependencies between the different

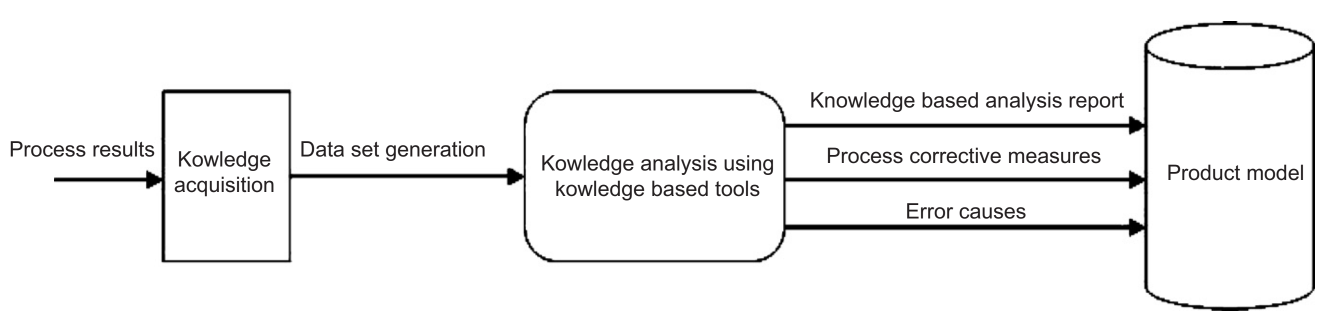

Fig. 5. Operational structure for learning algorithms.

Table 1
An example format of the partial data set for the analysis of the process control parameters

Part ID	Geometrical data				Operation type (STEP-NC)	Feedrate (mm/rev)	Cutting speed (rpm)	Depth of cut (mm)	Work piece material
	Feature ID	Dimension ($L/b/h$) mm	Diameter (mm)	Depth (mm)					
1	Pocket_1				$100 \times 50 \times 20$	—	—	Bottom_and	
					_side_rough_	0.1	1200	3	Al-6
Milling									
					Bottom_and _side_finishing	0.08	1400	3	
	Hole_1		5	10	Drilling	0.05	1000	5	
2	—	—	—	—	—	—	—	—	—
3	—	—	—	—	—	—	—	—	—

process parameters. In this regard, the following heuristic is to be employed.

Step 1: Set part_ID $i = 1$.

Step 2: Select two process parameters (a, b) for i.

Step 3: Determine the dependency level (D) between the selected parameters for i.

Step 4: Set the threshold value t.

Step 5: For process parameters (a, b), if $\min\{D\{(a, b),(b, a)\}\} < t$, remove the parameters for i and check the other parameters.

Step 6: Set $i = i+1$, if all part_IDs have been considered go to step 7;otherwise go to step 1.

Step 7: Terminate the algorithm and output the reduced data set

The dependency levels [43] of the process parameters indicate the effect of one process parameter over the other throughout the total observations and their impact over the optimised process parameters. The threshold value depends on the values obtained for the actual parameters in respect to the nominal process parameters. The threshold value is set in such a manner such that the redundant parameters in the data set can be eliminated.

(4) *Useful knowledge retrieval*: Clustering algorithms [44] such as K-mean clustering or C-mean clustering are applied to discrete process parameters of the reduced data set. This helps in clustering the parameters into different classes. Based on these classes, the decision rule generation algorithms are applied to extract the knowledge from the data set. These decision rules form a knowledge-based analysis report that will provide the corrective measures for the deviation in the process parameters that will enable the elimination of different types of errors resulting in the production of quality assured products.

7. Conclusions

This paper has presented and discussed the operational structure of STEP-NC compliant process control framework for discrete components. The authors have attempted to close the manufacturing loop by incorporating three types of process control in the framework. A knowledge-based analyser is proposed in the framework which analyses these process control data and provides the feed back for compensating the various types of errors such as static and dynamic errors and improving the surface quality of the parts. The paper also outlines the STEP-NC compliant information, which supports in achieving process control in CNC manufacturing. The importance of self-learning algorithms in achieving process control is recognised and a methodology is outlined for using the information from previously collected processing data to enable the feedback in framework.

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References

[1] ISO 10303-1. Industrial automation systems and integration-product data representation and exchange—Part 1: overview and fundamental principles 1994.

[2] Tsai Y-H, Joseph CC, Lou S-J. An in-process surface recognition system based on neural networks in end milling cutting operations. Int J Mach Tools Manufact 1999;39:583–605.

[3] Kurada S, Bradley CA. Review of machine vision sensors for tool condition monitoring. Comput Ind 1997;34:55–72.

[4] Chatterjee S. Spindle deflections in high-speed machine tools—modeling and simulation. Int J Adv Manufact Technol 1995;11:232–9.

[5] Brecher C, Vitr M, Wolf J. Closed loop CAPP/CAM/CNC process chain based on STEP and STEP-NC inspection tasks. Int J Comput Integr Manufact 2006;19(6):570–80.

[6] Drozda TJ, Wick C. Tool and Manufacturing Engineers Handbook, 4th ed., vol. 1. USA: Machining Society of Manufacturing Engineers; 1983.

[7] Gillespie LK. Troubleshooting manufacturing processes. USA: Society of Manufacturing Engineers; 1988.

[8] Yandayan T, Burdekin M. In-process dimensional measurement and control of work piece accuracy. Int J Mach Tools Manufact 1997;37(10):1423–39.

[9] Haber R, Peres C, Alique JR, Ros S. Fuzzy supervisory control of end milling process. Inform Sci 1996;89:95–106.

[10] Balic J, Kovacic M. Intelligent tool path generations for milling of free surfaces using neural networks. Int J Mach Tools Manufact 2002;42:1172–9.

[11] Yeo SH, Khoo LP, Neo SS. Tool condition monitoring using reflectance of chip surface and neural network. J Intell Manufact 2000;11:507–14.

[12] Rober SJ, Shin YC. Control of cutting force for end milling processes using an extended model reference adaptive control scheme. Trans ASME J Manufact Sci Eng 1996;118:339–47.

[13] Liu Y, Zuo L, Wang C. Intelligent adaptive control in milling processes. Int J Comput Integr Manufact 1999;12(5):453–60.

[14] Elbeheiry EM, Elmaraghy WH, Elmaraghy HA. A structured linear quadratic Gaussian based control design algorithm for machine tool controllers including both feed drive and process dynamics. J Vib Control 2005;11:949–83.

[15] Peng YH. On the performance enhancement of self turning adaptive control for time varying machining processes. Int J Adv Manufact Technol 2004;24:395–403.

[16] Masory O, Koren Y. Variable gain adaptive control system for turning. J Manufact Syst 1983;2:165–73.

[17] Ulsoy AG, Koren Y. Applications of adaptive control to machine tool process control. IEEE Control Syst Mag June 1989; 33–7.

[18] Koren Y. Comput Control Manufact Syst. New York: McGraw-Hill; 1983 [chapter 3].

[19] Wu CL, Haboush RK, Lyrnburner DR, Smith GH. Closed-loop machining control for cylindrical turning. Modeling, sensing and control of manufacturing systems. New York: ASME; November 1986. p.189–204.

[20] Yao B, Tomizuka M. Smooth robust adaptive sliding mode control for robot manipulators with guaranteed transient performance. ASME J Dyn Syst. Meas Control 1996.

[21] Butler J, Haack B, Tomizuka M. Reference generation for high speed coordinated motion of a two axis system. In: Symposium on robotics—1988 ASME Winter Annual Meeting, November 1988.

[22] Harmol A. Process diagnostic as a means of improving the efficiency of quality control. Product Plann Control 2000;11(8):797–805.

[23] Shin YC, Waters AJ. Framework of a machine advisory system with application to face milling process. J Intell Manufact 1998;9:225–34.

[24] Samuel GL, Shunmugam MS. Evaluation of circularity and sphericity from coordinate measurement data. J Mater Process Technol 2003;139(1-3):90–5.

[25] Chen AH, Kurfess TR. Integrated inspection and process control for machining a circular contour on a two-axis vertical turning lathe. Int J Manufact Res 2006;1(1):101–17.

[26] Stewart T. CNC machining magazine, touch probes: a good choice for closed-loop process control, Spring, vol. 3(9), URL: ⟨http://www.cncmagazine.com/⟩, 1999.

[27] Cassady CR, Bowden RO, Liew L, Pohl EA. Combining preventive maintenance and statistical process control: a preliminary investigation. IIE Trans 2000;32:471–8.

[28] Chin DH, Yoon MC. Detection of chatter in endmilling operation using wavelet transform. In: Proceedings of a CIRP seminar, 2004. p. 149–52.

[29] Corrigall MJ. Inspection plan and code generation for coordinate measuring machines in a product modelling environment. Doctoral thesis, Loughborough University, 1990.

[30] DMIS 3.0. Dimensional measuring interface standard. ANSI/CAM-I 101 1, 1995.

[31] ISO 6983/1. International Organization for Standardization. Numerical control of machines—Program format and definition of address words—Part 1: data format for positioning, line and contouring control systems, 1st ed, 1982.

[32] ISO10303-224. Industrial automation systems and integration-product data representation and exchange—Part 224: application protocol: mechanical product definition for process planning using machining features Geneva, Switzerland, International Organization for Standardization; 2000.

[33] ISO/DIS 10303-238. Industrial automation systems and integration—product data representation and exchange—Part 238: application protocols: application interpreted model for computerized numerical controllers, 2003.

[34] ISO 10303-203. Industrial automation systems and integration—product data representation and exchange—Part 203: application protocol: configuration controlled 3D designs of mechanical parts and assemblies, 1994.

[35] ISO/CD 10303-240. Industrial automation systems and integration: product data representation and exchange, Part 240: application protocol: process plans for machined products. CD-Ballot version, 2003 (ISO-Geneva).

[36] ISO10303-219 TC184/SC4/WG03-N1515,ISO/CD .Product data representation and exchange: application protocol: dimensional inspection information exchange. Geneva, Switzerlandl: International Organization for Standardization; 2005.

[37] ISO14649-10. International Standards Organization, TC184/SC1/WG7, ISO14649/FDIS. Industrial automation systems and integration—physical device control—data model for computerized numerical controllers—Part 10: general process data, 2002.

[38] ISO14649-16WD, International Standards Organization, TC184/SC1/WG7, ISO14649/FDIS. Industrial automation systems and integration—physical device control—data model for computerized numerical controllers—Part 16: data for touch probing based inspection, 2004.

[39] Suh SH, Cheon SU. A framework for an intelligent CNC and data model. Int J Adv Manuf Technol 2002;19:727–35.

[40] ISO14649-11, International Standards Organization, TC184/SC1/WG7, ISO14649/FDIS. Industrial automation systems and integration—physical device control—data model for computerized numerical controllers—Part 11: general process data for milling, 2002.

[41] Ramesh R, Mannan MA, Poo AN. Error compensation in machine tools-a review, part I: geometric, cutting-force induced and fixture-dependent errors. International J Mach Tools Manufact 2000; 40:1235–56.

[42] Quinlan JR. Induction of decision trees. Mach Learning 1: 81–106.

[43] Mohanty PS, Allor R, Lechowicz P, Parker R, Craig J. Particle temperature and velocity characterization in spray tooling process by thermal imaging technique. Thermal spray ASM. May. Ornaldo, FL, p. 1183–90.

[44] Kaungo T, Netanyaho NS, Wu AY. An efficient k-means clustering algorithm: analysis and implementation. IEEE Trans Pattern Anal Mach Intell 24(7); 887–92.