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# Manufacturing data analysis of machine tool errors within a contemporary small manufacturing enterprise

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## Abstract

The main focus of this paper is directed at the determination of manufacturing errors within the contemporary smaller manufacturing enterprise sector. These can manifest themselves as machine tool, fixturing or programming errors, experienced during the manufacture of 2 1/2D components on a 3-axis vertical machining centre. The manufacturing error diagnosis is achieved through the manufacturing data analysis of the results obtained from the inspection of the component on a co-ordinate measuring machine. This manufacturing data analysis activity adopts a feature-based approach and is conducted through the application of a forward chaining expert system, termed, the Product Data Analysis Distributed Diagnostic Expert System, which forms part of a larger prototype feedback system entitled the Production Data Analysis framework. This paper introduces the manufacturing error categorisations that are associated with milling type operations, knowledge acquisition and representation, conceptual structure and operating procedure of the prototype manufacturing data analysis facility. The paper concludes with a brief evaluation of the logic employed through the simulation of manufacturing error scenarios. This prototype manufacturing data analysis expert system provides a valuable aid for the rapid diagnosis and elimination of manufacturing errors on a 3-axis vertical machining centre in an environment where operator expertise is limited. 

*Keywords:* Manufacturing data analysis; Expert systems; Feature based manufacturing; Machining tool error detection and diagnosis; Computer aided inspection

## 1. Introduction

It has been recognised that inspection and measurement of manufactured parts is undertaken for two main reasons [1]:

(i) Product control—to verify conformance of the component to the design intent;
(ii) Process control—to provide feedback to achieve tighter control of previous manufacturing processes.

As a consequence of increased customer pressure for improved quality at reduced cost, an ideal closed loop manufacturing system requires to encompass both the product and process control inspection scenarios and must incorporate the following [2]:

(i) Part measurement;
(ii) Determination of geometric errors through comparative tolerance analysis;
(iii) Determine the most probable production cause for geometric errors; and
(iv) Recommend corrective actions to eradicate the problem.

The scope and diversity of these requirements for these systems tend to be unique and result in complex installations that can only be applied within large companies whose business activities are deterministic in nature. However, with the continuing reduction in cost, coupled with the dramatic increase in processing power, of modern computing systems these CIM installations are now becoming viable for the smaller manufacturing

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enterprises (SME's) to exploit. Due to the complicated and expensive structure of such systems these cannot be readily scaled down and directly applied to the volatile and mult-disciplinary operating environment experienced within a contemporary metalworking SME.

This paper outlines research into closing the manufacturing feedback loop which is specifically directed at the contemporary metalworking SME and focuses on the diagnosis of manufacturing and machine tool errors. This is achieved through the manufacturing data analysis from geometric errors obtained by the inspection of 2 1/2D prismatic components on a co-ordinate measuring machine (CMM). This analysis activity forms the final part of a larger manufacturing, inspection and analysis system known as the Production Data Analysis (PDA) framework [3].

## 2. Machine tool error diagnosis

Machine tool error diagnosis is the troubleshooting activity of diagnosing either faults due to the manufacturing process or errors that occur due to the malfunction of some elements of the machine tool. The methods employed to achieve this can be classified into two distinct categories: the condition monitoring of machine tools by using sensory data and the inferring of machine tool errors through the inspection and manufacturing data analysis of components produced by a number of operations conducted on the machine tool. This paper introduces research into the classification of machine tool errors and outlines contemporary experimental research into diagnosing these manufacturing errors through both condition monitoring and manufacturing data analysis diagnostic approaches.

### *2.1. Manufacturing fault classification*

In order to conduct a diagnostic troubleshooting exercise on a machine, one must first be aware of the possible machining errors that can occur during the machining process. Drozda and Wick [4] and Gillespie [5] undertook a comprehensive study of the operating parameters and the machining errors for the whole spectrum of manufacturing processes. In general machining tool errors can be categorised into one of two classes: random or stochastic errors and systematic errors [6]. Random or stochastic errors are the type that cannot be controlled by the operator and comprise the variations within the machine tool and the application variations introduced during its use. These errors can be attributed to a combination of the machine's structural integrity, condition and the errors due to the operator or control system. Systematic errors represent errors that cause a significant drift of measured results obtained from a number of workpieces over a period of time. Typical systematic errors include: thermal distortions of machine tools, tool wear, deflections of the machine/tooling/workpieces during machining, deflection of machine tool due to workpiece's weight and misalignment of the machine tool's axes.

### *2.2. Condition monitoring of manufacturing machine tools*

Condition monitoring can be defined as the real-time activity of observing sensory information to monitor either the machine tool condition or to monitor the machining process itself. Condition monitoring techniques can be applied to observe machine process parameters such as motor horsepower, cutting force, cutting temperature, vibration and acoustic emissions.

Vibration monitoring of tool failure proves to be the most popular method for the condition monitoring of cutting tool failure. El-Wardany et al. [7] employed vibration signature analysis techniques for the monitoring of tool failure in drilling operations on cast iron test pieces using a YAM $2^1/_2$ axis CNC machining centre. Moore and Kiss [8] also employed vibration monitoring techniques for the detection of carbide insert fracture of a three carbide tipped face-mill on a mild steel workpiece. The vibration signature of tool wear is also utilised by Nicolescu and Bejhem [9] for the on-line tool condition monitoring of turning operations, which employs statistical methods to compute the tool wear index for monitoring tool life.

An alternative method for the diagnosis of tool wear is that proposed by Konrad et al. [10] that involved the use of cutting forces to determine tooling faults of carbide tipped cutters in milling. From cutting force measurements a force model is constructed that enables parameters to be estimated for each insert of the milling cutter. A classification algorithm analyses the pattern of the parameters in order to categorise insert condition into one of four classes: normal cutting, wear, breakage and radial insert initial displacement. Jemielniak et al. [11] also employed cutting forces and acoustic emissions for tool wear diagnosis. These cutting parameters form the input to feed a forward, back propagation neural network.

A system for estimating and in-process compensation of manufacturing process errors in CNC machining was proposed by Zhou et al. [12] that uses a neural network combined with a linguistic rule-based fuzzy controller. They employ a three stage method, that involves calibration, learning or training, and real compensation, to neutralise process errors caused by inherent geometric errors of the machine tool, process dependent and environment errors.

An expert system for diagnosing faults in CNC machine tools is proposed by Bohez and Thieravarut [13]. The diagnostic model employed in this approach used a hybrid reasoning method that utilises both deep and shallow knowledge models. The shallow model represents the heuristic fault knowledge whilst the structure and behaviour of the CNC system is represented within the deep model. The expert system utilises a combination of the maintenance manual procedures to diagnose controller malfunctions and relay ladder logic and electrical diagrams for the diagnosis of machine tool failures.

The aforementioned review of condition monitoring techniques is by no means exhaustive [14], however it is intended to provide the reader with an appreciation of the diverse approaches the can be adopted to provide real-time control of manufacturing processes and machine tools. Other condition monitoring examples that relate to the maintenance and process control of CNC machine tools and Flexible Manufacturing Systems (FMS) include: Puetz and Eichhorn [15], Majstorovic and Milacic [16], Lee [17], and Ye [18].

### *2.3. Manufacturing data analysis of production errors*

Manufacturing data analysis (MDA) has been defined by Lee [17] as the *"analysis and feedback of manufacturing data"* and is directed toward the determination of production errors, causes and the provision of corrective action feedback from geometric deviations obtained from the inspection of a component part.

An early attempt to address the problem of manufacturing data analysis was the closed loop inspection system for sculptured surfaces proposed by Van den Berg [19], who identified that MDA consists of two stages:

(i) matching of the observed errors with the possible sources of error contained in a manufacturing process model; and
(ii) Applying a corrective strategy to the manufacturing process.

Van den Berg [20] later elaborated and applied this initial proposal to the shape error compensation to tooling for both CNC milling and the formed tooling used in electro-chemical machining. The approach is employed for first-off component manufacturing of airfoil type components and involves a tool path correction algorithm, known as TOPAC, that produces a corrected shaping plan if shape errors are detected.

Pfeifer and Held [21] proposed a backward chaining expert system designed to diagnose the type, location, fault causes and recommended ways of eliminating them. The off-line prototype expert system relies on human interaction to establish potential fault causes, locations and remedies. This approach employs a static diagnostic decision tree to represent and assign geometric features to specific machine components responsible for producing them.

Anjanappa et al. [2,22] applied a procedural rule-based approach in the development of their Computer-Aided Inspection Data Analyser (CAIDA) at the University of Maryland. This PC-based diagnosis approach attempts to determine milling operation errors from both individual and combined feature dimensional inaccuracies determined by the inspection of a component part on a CMM. The system is feature-based and supports the diagnosis of cutting tool errors, machine tool errors, fixture/workholding errors and miscellaneous errors for hole, slot and pocket type features. Individual error analysis involves the boundary size, slot and pocket edge analysis, $X$ and $Y$ hole position analysis and hole and diameter analysis of an individual feature and is capable of identifying cutting tool, machine tool, fixture set-up and stock boundary errors. Combined error analysis is an attempt to filter out any incorrect error assertions and comprises of two analyses: combined tool error analysis and combined machine and fixture analysis.

MDA research undertaken by Lee and Bell [23] on data feedback in an integrated design to manufacture system provides the analysis of any deviated results determined by inspection and recommends appropriate actions should errors occur. This activity is supported by the product data model and employs decision trees associated with each feature and operates by analysing measured data held within the measurement graph of the product model with the component nominals in order to classify them into either upper-fault, satisfactory and lower-fault SPC type categories. The decision network is utilised to establish fault codes that are associated with a fault type, cause, for a fault cluster held within a fault library. The user is then presented with an ordered list comprising of the probable causes and suggested courses of action for each manufacturing error detected.

Kramer and Nadanasundaram [24] report another example of the application of a goal oriented backward chaining rule-based expert system. This human interactive system's problem domain is focused on the diagnosis of defects in milled components and was constructed using the PC Plus expert system shell. This prototype system can suggest corrective actions for nineteen possible common defects, such as chatter, rough surface finish and dimensional inaccuracies, from workholding device, cutting tool, machine tool and general error categories.

Another attempt at addressing the problem of interpretation of manufacturing errors from measured data obtained from the inspection of a component was established at Brunel University [25,26]. This approach was validated with the aid of the RASOR constraint modeller and was capable of identifying plausible manufacturing errors from the decomposition of the manufacturing process into a simple hierarchical tree structure consisting of four levels namely: part level, set-ups level, tools level, and features level.

A rule-based expert system has been developed by Luong et al. [27], which uses the VP Expert system shell for the diagnosis of defects in plastic injection moulding. The system basically consists of a dbase IV database, an inference engine, and a knowledge base, which is constructed using 47 production type rules. The system is capable of diagnosing one of a possible 10 production faults. As with the expert system devised by Kramer and Nadanasundaram [24], this system relies totally upon the inputs supplied by the user to a set of predefined questions to direct the diagnosis.

Although the research contributions reported in Section 2.3, employs some facet of artificial intelligence to conduct the MDA activity it must be mentioned that there is a significant amount of research being conducted into the performance monitoring and final cut compensation schemes. This is achieved through the application of an in-process part measurement technique and includes contributions from: Fan et al. [28], Mayer et al. [29], and Yandayan and Burdekin [6,30].

## 3. The production data analysis framework

The proposed PDA framework is specifically aimed to close the quality information feedback loop and support the multi-disciplinary working practices experienced within a contemporary SME that cannot be achieved by the rigid scaled down versions of software applications employed within larger companies. To achieve the objectives of this research the prototype PDA framework encompasses five vital issues that are considered essential to occupy the information feedback loop void that currently exists within any contemporary manufacturing systems, namely [3,31]:

(i) Machine and inspection planning;
(ii) Production code generation;
(ii) Comparative tolerance analysis;
(iv) Manufacturing data analysis (MDA);
(v) Data resource model integration.

The focus of this paper concentrates upon the manufacturing data analysis phase of a prototype production data analysis facility known as the Production Data Analysis Distributed Diagnostic Expert System (PADDES). The MDA functionality is based upon the outcome of the comparative tolerance analysis activity and analyses the inspection results and the component status category obtained from the tolerance analysis report and interrogates the machine dependent fault library information residing in the manufacturing model in order to establish:

(i) machine dependent production errors;
(ii) probable cause for the production errors; and
(iii) recommended corrective actions to be taken for the machine in question.

The ascertained machine dependent production error, cause and action taken are logged onto the manufacturing model's historical log for that machine. This information can be utilised at the planning stage to ascertain the most appropriate machine to undertake the operation or to initiate unplanned maintenance of the machine tool. This functionality provides the capability to initiate procurement of additional materials for rejected components, together with the rescheduling and regeneration of NC and inspection programs for re-workable components. Based on the fundamentals of MDA, the concept of reactive manufacturing control can be realised through the effective information integration and manufacturing error feedback.

## 4. Production data analysis distributed diagnostic expert system (PADDES)

The MDA functionality of PADDES is based upon the component's geometric error information generated by the comparative tolerance analysis phase of the prototype PDA facility. PADDES utilises the machine dependent knowledge base rules, contained within the manufacturing in a forward chaining process to infer production errors, and remedial actions from the inspection of 2 1/2D prismatic parts. The ascertained machine dependent production error, cause and action taken is logged onto the manufacturing model's historical log for that machine.

### 4.1. Expert system development tool

The PADDES phase of the prototype PDA framework employs the C Language Integrated Production System (CLIPS) version 6.1 expert system tool, developed originally by NASA [32–34], to conduct the manufacturing data analysis activity. This expert system shell provides a forward chaining inference strategy based on the Rete algorithm that is ideally suited to the automatic diagnosis of production errors from inspection related information. CLIPS employs two programming paradigms: procedural programming and object-oriented programming the latter of which is termed the CLIPS Object-Oriented Language (COOL). PADDES performs the diagnosis of manufacturing errors from the inspection results by utilising all the procedural, rule-based and object-oriented capabilities provided by the CLIPS expert system shell.

The structure of PADDES follows the standard expert system configuration and consists of: a working memory, a knowledge base and an inference engine. PADDES employs COOL's object-oriented fact representation of

CLIPS to portray the actual state or condition of the component, which is generated during the comparative tolerance analysis activity of the prototype PDA framework. This comparative tolerance analysis fact file comprises feature class definitions and the instances of the classes that correspond to the inspected construction feature objects of the component which constitutes the fact input to PADDES and are temporarily stored within the short term or working memory of the expert system.

### *4.2. PADDES manufacturing error categorisation*

A comprehensive categorisation of the types of manufacturing errors regarding the milling process is expressed in Fig. 1. This categorisation is based upon the error classifications identified in Section 2.1 and consists of: cutting tool errors, fixturing and work holding errors, machine tool errors, miscellaneous errors, and a completely new area of programming errors.

The milling production errors are further classified into categories that effect the geometric characteristics of a component. These categories include the type of error that can effect individual features and those that effect all the features of a component.

(i) *Individual feature errors* are those that affect only one feature and include: cutting tool errors such as tool size error, tool run-out/misalignment error, tool wear and tool deflection. Programming errors such as feature size error, feature position/orientation error and interpolation error; and finally miscellaneous errors that relate to cutting conditions such as chatter and workpiece deflections are also included.

(ii) *Combined feature errors* comprise of the errors that propagate through the entire component and involve: machine tool errors such as axis out-of-calibration errors, servo lag/interpolation errors, stiffness errors, thermal distortion errors and random or stochastic type errors. Fixturing and workpiece deflection errors include: set-up errors between component and machine, fixture and machine and component and machine interfaces and insufficient chip control. Miscellaneous errors arising from dimensional errors of the stock material are also categorised.

The approach adopted by PADDES whilst conducting a consultation is directed towards the attainment of the individual feature errors of cutting tool type and programming type for each attribute of a feature and for all features that constitute the component part. The manufacturing data analysis of PADDES is only initiated if the feature attribute contained within the comparative tolerance analysis fact file under scrutiny possesses a defective quality status of either REJECT or REWORK. A second analysis phase of PADDES is concerned with the determination of possible combined feature errors of machine tool type, out-of-calibration of axes and component set-up error.

### *4.3. Knowledge acquisition and representation of PADDES*

Although there are numerous methods of acquiring the knowledge to emulate the human expert, the method adopted in this research comprised of extracting the required generic information from manufacturing handbooks and tooling catalogues. These included the Society of Manufacturing Engineers' publications: Tool and Manufacturing Engineers Handbook [4] and Troubleshooting Manufacturing Processes [5]. The manufacturing process information presented by these publications is comprehensive, however the specific information extracted for use by PADDES has been restricted to the generic manufacturing operations that can be conducted on a three axis milling type with operations such as: milling, drilling, boring, and reaming.

The knowledge extracted from the Tool and Manufacturing Engineers Handbook and the Troubleshooting

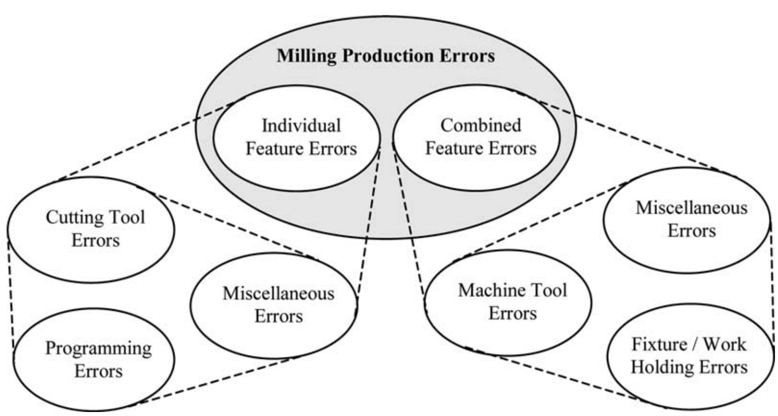



Fig. 1. Feature-based production errors applicable to the milling process.

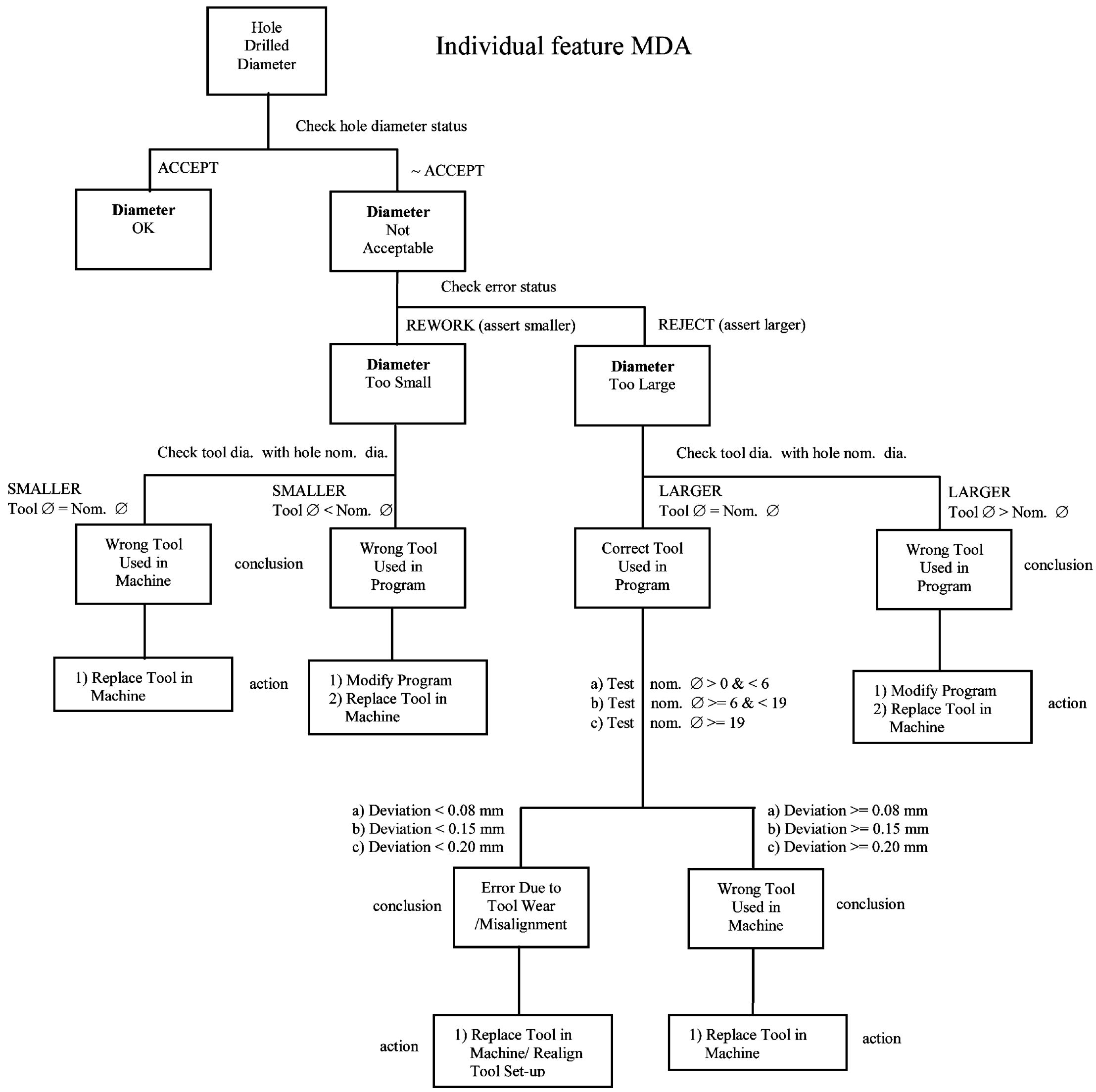



Fig. 2. Logic decision tree for diagnosis of diameter errors of a drilled hole.

Manufacturing Processes publications have been represented in the form of decision or logic trees. These tree diagrams, as depicted for the diameter of a hole type feature in Fig. 2, provide a graphical portrayal of the logic embedded within the long-term memory, known as the knowledge base, of the PADDES expert system. Each geometric attribute of every feature supported by the prototype PDA framework has a decision tree associated with it in PADDES. The decision tree illustrates how the logic captured by the knowledge base is applied to the component feature facts held within the working memory of PADDES.

## 5. Operational structure of the PADDES expert system

The operational structure of the manufacturing data analysis activity conducted by the PADDES expert system is pictured in the IDEF0 graphical representation of Fig. 3 [3]. The MDA functionality of the PDA framework is based upon the outcome of the comparative tolerance analysis phase. The MDA activity utilises the machine dependent knowledge base rules, contained within the PDA manufacturing model to infer production errors, and remedial actions from the inspection of 2 1/2D prismatic parts. The ascertained machine dependent production error, cause and action taken is logged onto the PDA manufacturing model's historical log for that machine. This information is subsequently utilised at the planning stage to ascertain the most appropriate machine to undertake the operation or to initiate unplanned maintenance of the machine tool and to plan reclamation work. This activity consists of four major activities namely:

(i) Obtain component feature fact file;
(ii) Obtain machine fault library;

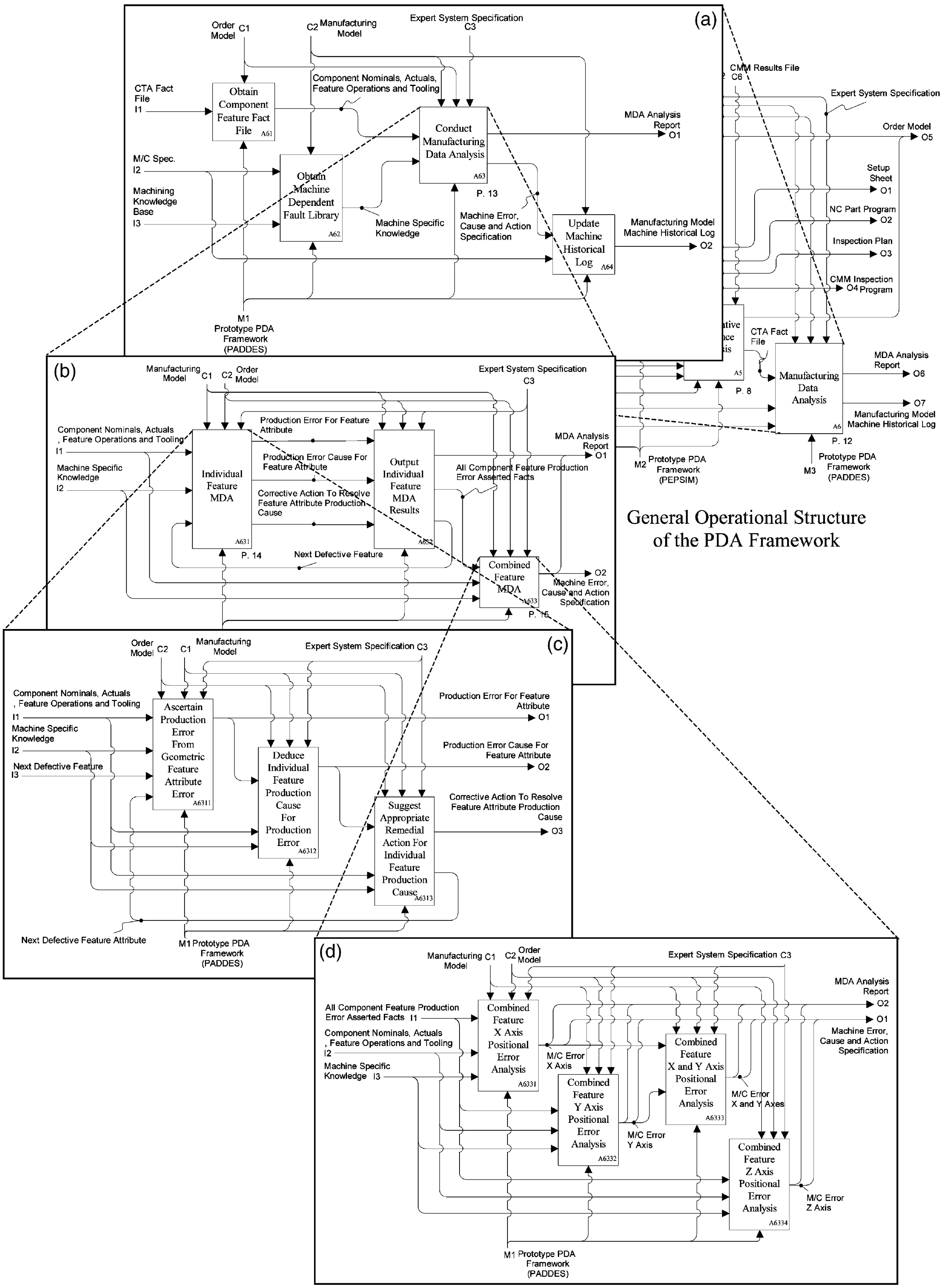



Fig. 3. IDEF0 representation of the manufacturing data analysis functionality of the PDA framework.

(iii) Conduct MDA; and
(iv) Update machine historical log.

### 5.1. Obtain component feature fact file

The component feature fact file created by the comparative tolerance analysis phase of the prototype PDA framework contains all the necessary nominal and actual feature attributes and operational data generated by the planning, manufacture, inspection and analysis activities and represents the current condition of the component. No other data needs to be supplied by the user regarding the condition of the component during the consultation.

### 5.2. Obtain machine dependent fault library

This activity is concerned with the input of the diagnostic decision logic expressed by the complete collection of decision trees for both individual and combined feature error diagnosis and implemented in the MDA expert system as diagnostic rules. The diagnostic rules are obtained for each machine tool from the PDA manufacturing model [3]. These rules constitute the domain knowledge contained within the expert's systems knowledge base. Upon loading of the knowledge base the rules are examined to establish which rules will fire and these are placed in order of priority on an agenda for execution.

### 5.3. Conduct manufacturing data analysis

Manufacturing data analysis is initiated once both the component feature instances have been defined and the knowledge base has been populated with the machine dependent diagnostic rules. The logic followed by the execution of the consultation consists of individual feature manufacturing data analysis and combined feature manufacturing data analysis.

#### 5.3.1. Individual feature MDA diagnosis

The MDA diagnosis is conducted for every attribute for each feature in a defined order of priority. Any production error, cause and suggested corrective action conclusions are appended to the analysis output file during the consultation giving a running record of the analysis. This activity is the initial diagnosis function performed by PADDES and involves the diagnosis of manufacturing errors in the form of tooling and component set-up errors for each attribute for every individual feature documented within the comparative tolerance analysis fact file, depicted as a closed blind rectangular pocket feature in Fig. 4. The feature attributes employed in the individual feature MDA diagnosis of such a pocket feature within PADDES includes: combined pocket length and width, pocket depth, pocket orientation and pocket position in the *X*, *Y* and *Z* axes.

The logic decision tree representation of the knowledge base rules for the diagnosis of tool and program based manufacturing errors for both the length and width of a closed key slot or a closed blind rectangular pocket feature is depicted in Fig. 5. The logic represented by the decision tree shown in Fig. 6a has been tested by altering the feature attribute values stated within the comparative tolerance analysis fact file to invoke the desired response from the logic captured within the PADDES's knowledge base. The modifications to the feature-based comparative tolerance analysis fact file for a closed blind rectangular pocket (PK—000), documented in Fig. 4, to invoke the logic shown in Fig. 5(a), is as follows:

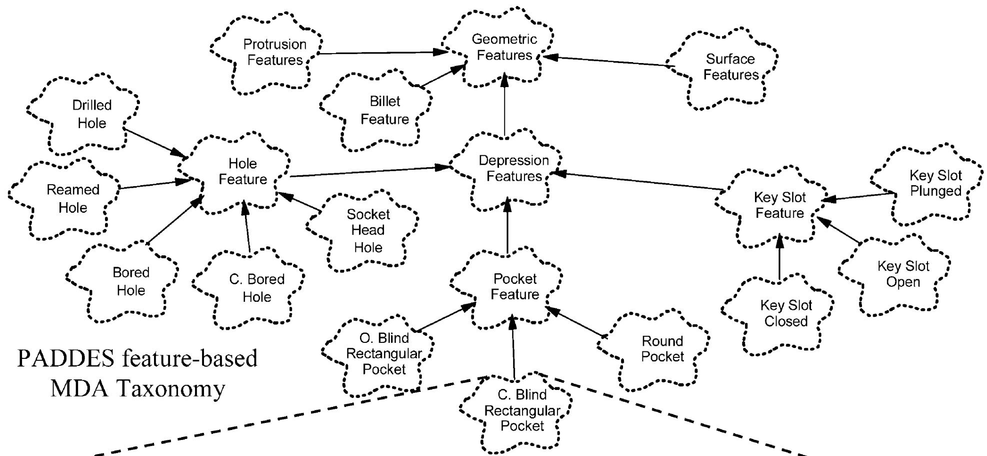
(act—pock—length 40.5)
(pock—length—deviation 0.5)
(pock—length—tol—status OUTOL)
(quality—status—length REJECT)
(act—pock—width 39.5)
(pock—width—deviation −0.5)
(pock—width—tol—status OUTOL)
(quality—status—width REWORK)

These modifications specify that the length of the pocket is too large whilst the width is too small thus invoking the diagnostic response documented in Fig. 6(a). As PADDES conducts the diagnostic consultation, the dialogue window and the output (.paddes) file reflects the step by step execution of the diagnostic process. New facts that are asserted into the PADDES working memory are employed to direct subsequent diagnosis depicted in the fact window of Fig. 6(a). It can be seen that the asserted facts for both the larger length and smaller width of the pocket initiated the combined length and width interpolation error conclusion and action logic, shown in Fig. 5(a) to be asserted.

The simulation of an oversized tool in Fig. 5(b) employed in the manufacture of the closed blind rectangular pocket (PK—000) can be achieved through the modification of the pocket extract of the feature-based comparative tolerance analysis fact file illustrated in Fig. 4:

(act—pock—length 40.55)
(pock—length—deviation 0.55)
(pock—length—tol—status OUTOL)
(quality—status—length REJECT)
(act—pock—width 40.545)
(pock—width—deviation 0.545)
(pock—width—tol—status OUTOL)
(quality—status—width REJECT)

These modifications reflect that the pocket length and width deviations are equal to within certain limits and greater than 0.5 mm above nominal size. Thus the pocket




**Comparative Tolerance Analysis Fact File**

```
(definstances POCKET_OBJ_PK_000
(PK_000 of C_B_R_POCKET
  (feature_name PK_000)
  (feature_type PCBR)
  (feature_count 1 )
  (feature_priority 1 )
  (no_p_points 32 )
  (datum_feature None      )
  (nom_ins_pntx 50 )
  (nom_ins_pnty 50 )
  (nom_ins_pntz 0 )
  (nom_rot_x 0 )
  (nom_rot_y 0 )
  (nom_rot_z 45 )
  (nom_pock_length 40 )
  (nom_pock_width 40 )
  (nom_pock_depth 10 )
  (nom_pock_cdia 10 )
  (nom_pock_brad 0 )
  (act_ins_pntx 49.97868 )
  (act_ins_pnty 50.03832 )
  (act_ins_pntz 0.00572 )
  (ins_deviation_x -0.02132 )
  (ins_deviation_y 0.03832 )
  (ins_deviation_z 0.00572 )
  (tol_status_x INTOL)
  (tol_status_y INTOL)
  (tol_status_z INTOL)
  (quality_status_x ACCEPT)
  (quality_status_y ACCEPT)
  (quality_status_z ACCEPT)
  (act_rot_z 44.97313 )
  (rot_z_deviation -0.02687 )
  (rot_z_angle_tol_status INTOL)
  (quality_status_rot_z ACCEPT)
  (act_pock_length 39.92774 )
  (pock_length_deviation -0.07226 )
  (pock_length_tol_status INTOL)
  (quality_status_length ACCEPT)
  (act_pock_width 39.92154 )
  (pock_width_deviation -0.07846 )
  (pock_width_tol_status INTOL)
  (quality_status_width ACCEPT)
  (act_pock_depth 9.91984 )
  (pock_depth_deviation -0.08016 )
  (pock_depth_tol_status INTOL)
  (quality_status_depth ACCEPT)
  (pock_base_flatness 0.0093262 )
  (b_flat_tol_status INTOL)
  (quality_status_b_flat ACCEPT)
  (act_pock_cdia 9.8859 )
  (pock_cdia_deviation -0.11412 )
  (pock_cdia_tol_status INTOL)
  (quality_status_cdia ACCEPT)
  (pock_cdia_circularity 0.0072178 )
  (cdia_circ_tol_status INTOL)
  (quality_status_cdia_circ ACCEPT)
  (act_pock_brad 0 )
  (pock_brad_deviation 0 )
  (pock_brad_tol_status ACCEPT)
```

```
(quality_status_brad ACCEPT)
(pock_brad_circularity 0 )
(brad_circ_tol_status      )
(quality_status_brad_circ      )

(op1_data CSR s rfc pos 14 z0 z-10 n0 k20001 l.5 x0 y0 f r0)
(op1_mc_stage CSR)
(op1_mc_sstage s)
(op1_op_type rfc)
(op1_mc_mode pos)
(op1_stepover 14)
(op1_st_depth 0)
(op1_f_depth -10)
(op1_peck_depth 0)
(op1_b_curve k20001)
(op1_loff_all .5)
(op1_x_entry x0)
(op1_y_entry y0)
(op1_f_type f)
(op1_bott_rad r0)
(op1_comment ROUGH
(op1_tool_data SLT N D
(op1_t_type SLT)
(op1_t_search N)
(op1_t_majdia 20)
(op1_t_lgh 20)
(op1_sp_speed 509)
(op1_v_feed 22.4)
(op1_h_feed 90.6)
(op1_z_peck -14)
(op1_t_teeth 2)
(op1_t_matl M7)
(op1_t_desc SLOT DRILL M7 D20 * 20)

(op2_data csr s cnc pos z0 z-10 n0 ak20001 l0 e5.0)
(op2_mc_stage csr)
(op2_mc_sstage s)
(op2_op_type cnc)
(op2_mc_mode pos)
(op2_st_depth 0)
(op2_f_depth -10)
(op2_peck_depth 0)
(op2_b_curve ak20001)
(op2_loff_all 0)
(op2_entry_dist e5.0)
(op2_comment FINISH AROUND)
(op2_tool_data SLT N D8 H13 N1273 V20.37 H63.65 Z-5 E2 T 'M7' 'NEW SLOT DRILL M7 D8 * 13')
(op2_t_type SLT)
(op2_t_search N)
(op2_t_majdia 8)
(op2_t_lgh 13)
(op2_sp_speed 1273)
(op2_v_feed 20.37)
(op2_h_feed 63.65)
(op2_z_peck -5)
(op2_t_teeth 2)
(op2_t_matl M7)
(op2_t_desc NEW SLOT DRILL M7 D8 * 13)

))
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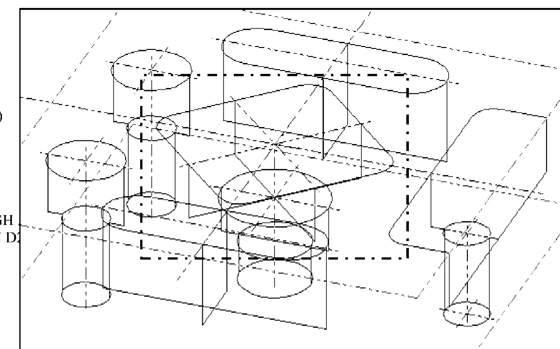


Fig. 4. Comaprative tolerance analysis fact file extract for a rectangular feature.

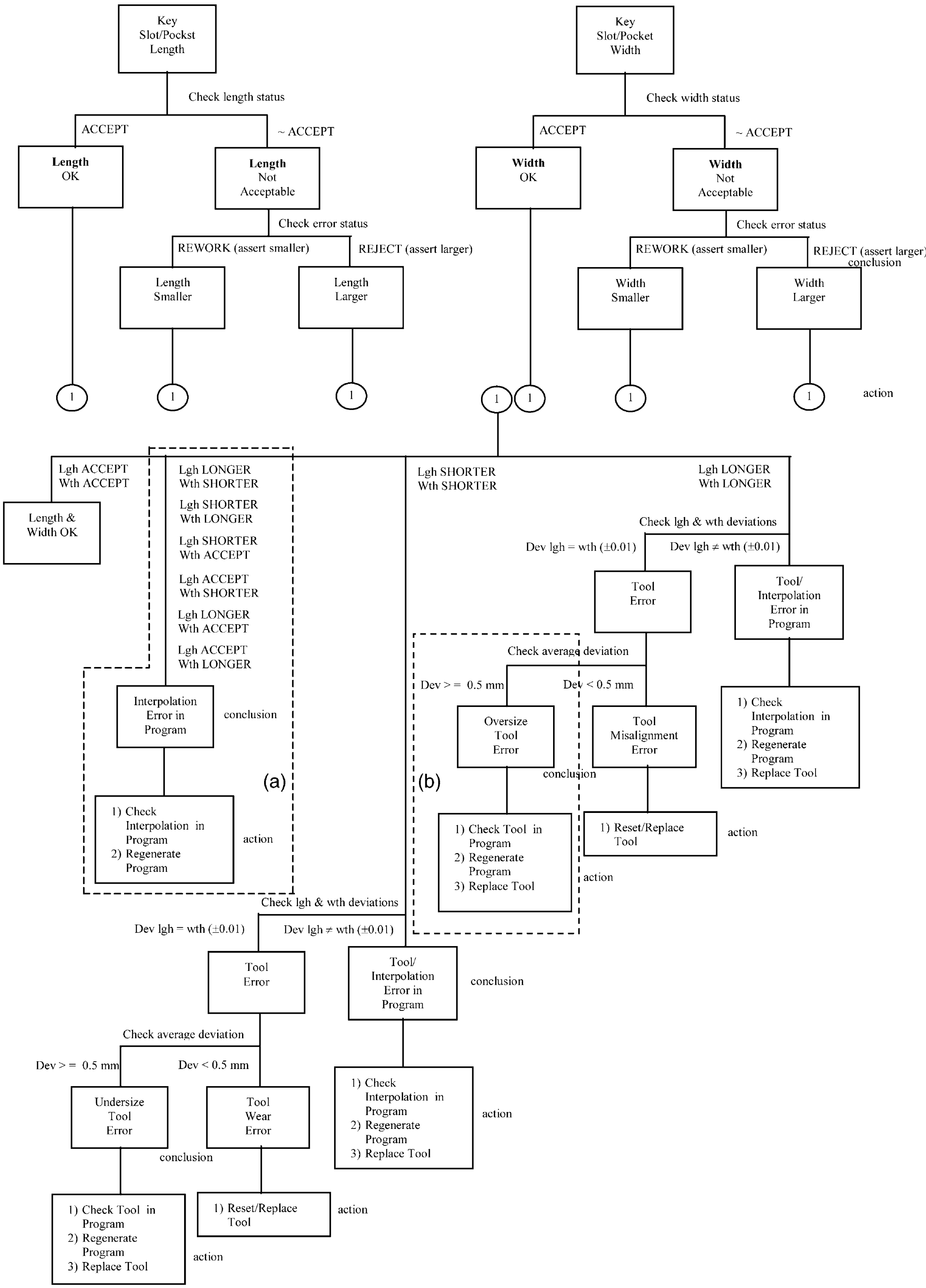
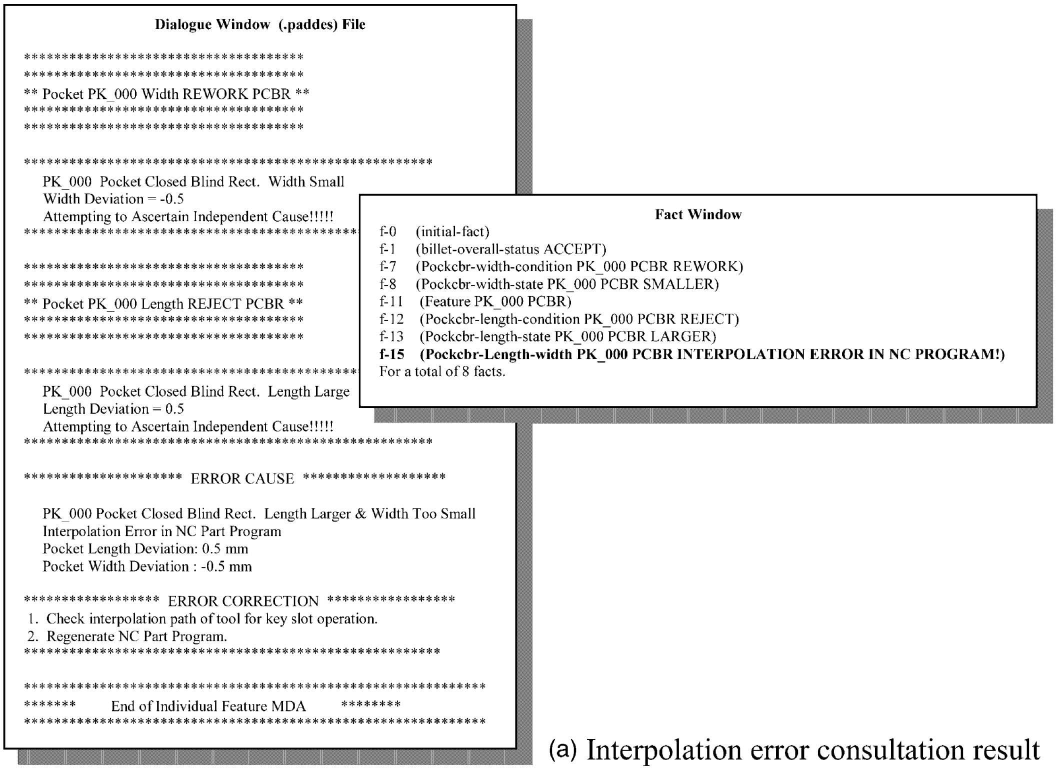
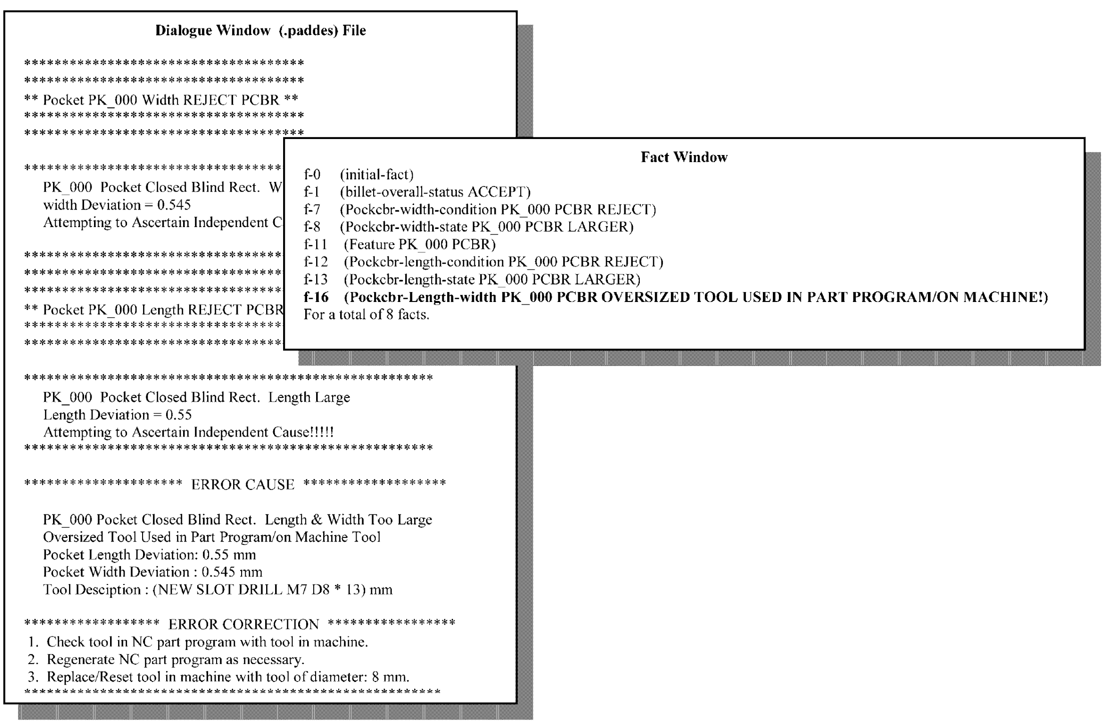



Fig. 5. Logic decision tree for diagnosis of the length and width of a rectangular pocket feature.




(a) Interpolation error consultation result




(b) Oversized tool used in part program consultation result

Fig. 6. PADDES consultation results for a rectangular pocket feature.

length and width are both designated as out-of-tolerance and assigned a feature quality status of reject. The result of the diagnostic consultation for the oversize tool error of a closed blind rectangular pocket type feature is documented in Fig. 6(b).

### *5.3.2. Combined feature MDA diagnosis*

Combined feature manufacturing data analysis is initiated upon completion of the individual feature analysis and its main purpose is to analyse the asserted positional facts generated by the individual feature MDA diagnostic activity logic. This is undertaken in an attempt to establish machine tool errors and to reinforce the diagnostic assertions produced through the individual feature analysis. The logic representation of the combined feature MDA diagnosis activity for both the X and Y axes are represented by the decision logic tree diagram depicted in Fig. 7. This analysis checks all feature positional status assertions in the *X* axis, then the *Y* axis, the combinatory effect of both the *X* and *Y* axes and finally the *Z* axis. The *X* and *Y* axes analysis is primarily concerned with the checking of positional errors to try and infer machine out-of-calibration or component set-up error from the individual feature positional errors. The *Z* axis analysis examines all the asserted *Z* axis facts of the features inserted directly onto the top face of the billet in an attempt to identify component set-up and billet size anomalies. If a conclusion can be drawn from this activity the individual feature position conclusions are retracted and a new combined feature conclusion is asserted. This combined conclusion is also appended into the machine dependent historical log of the PDA manufacturing model giving an up-to-date record of the machine's performance.

The simulation modifications applied to test the positional errors in the X axis involves all of the inspected features that comprise the geometry of the component. These feature insertion point modifications that represent the machine tool out of calibration error, as in Fig. 7(a) are applied to all the primary features, i.e. features inserted on the top face of the billet only, of test component and include:

(act—ins—pntx 51.5)
(ins—deviation—x 1.5)
(tol—status—x OUTOL)
(quality—status—x REJECT)

These modifications to the comparative tolerance analysis fact file simulates that all the primary features of a test component are out of position along the *X* axis by 1.5 mm. The initial asserted facts generated from the individual feature MDA diagnosis (a), PADDES consultation result fragment (b), and the additional fact asserted during the combined feature MDA diagnosis (c) for the machine out of calibration error are documented in Fig. 8.

The manipulation of the attributes to simulate a component set-up error in the *X* and *Y* axis involves the modification of the *X* primary feature insertion positions

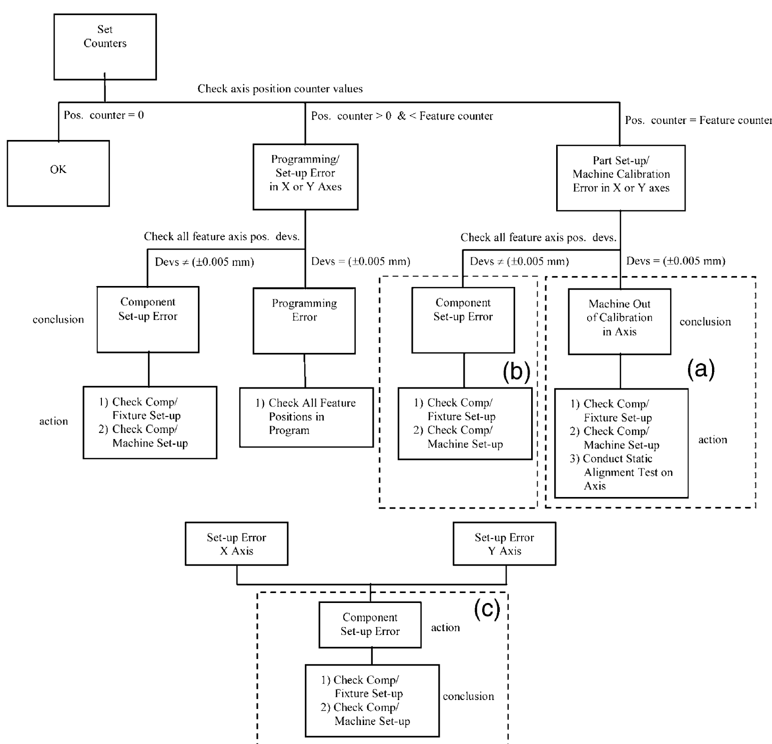



Fig. 7. Logic decision tree for combined MDA diagnosis of the position in the *X* and the *Y* axes of the individual feature MDA asserted facts.

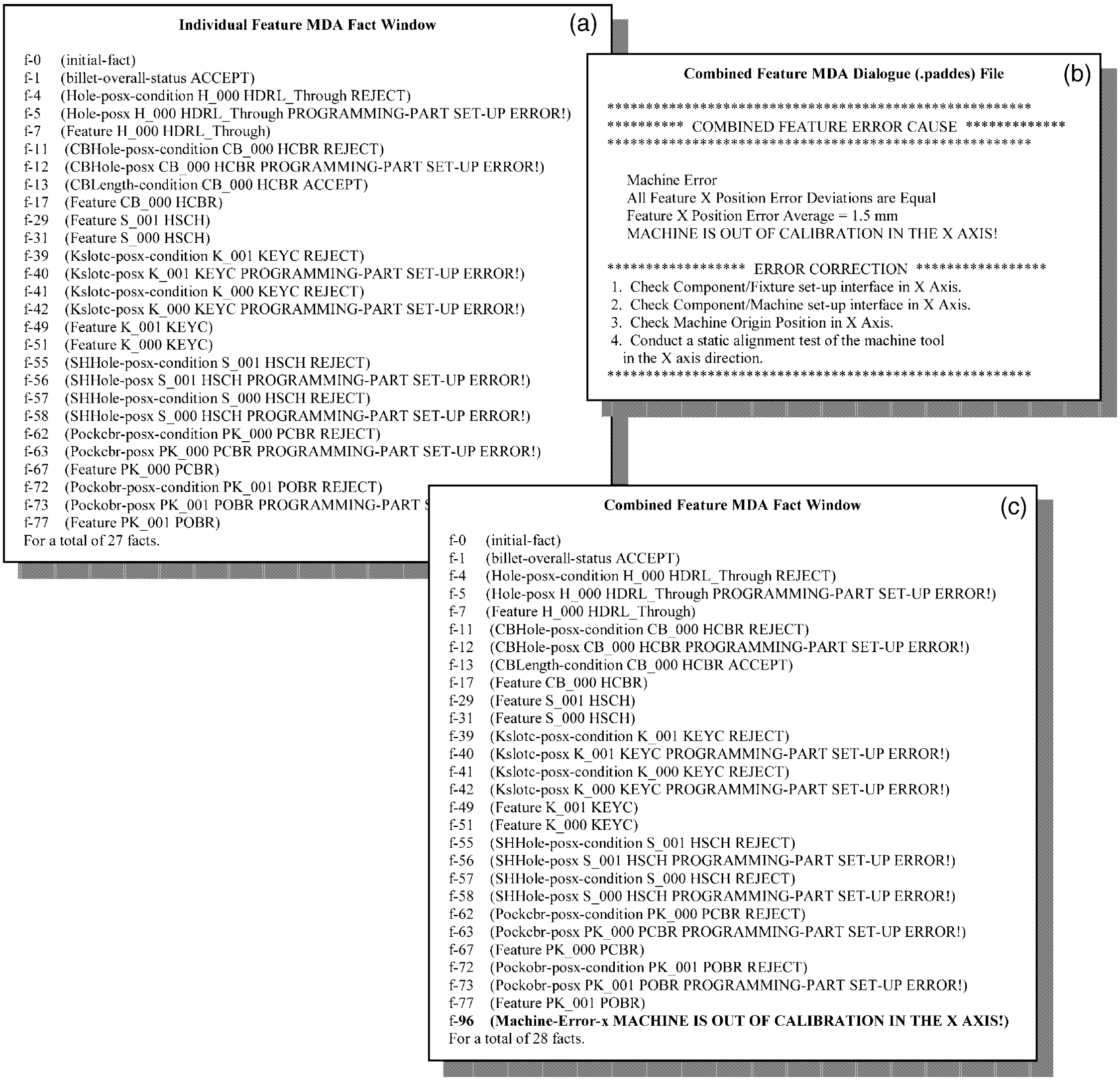



Fig. 8. PADDES consultation output of the combined feature analysis of the machine is out of calibration error scenario of the *X* axis.

within the comparative tolerance analysis fact file to represent a component set-up error. This is achieved through simulating a slightly skew effect by giving each primary feature of the component different *X* and *Y* insertion point deviations in order to rule out the machine out of calibration in the *X* and *Y* axes error scenarios. The insertion point deviation values employed to simulate this scenario range from 1.0 mm for the left-hand features, 1.5 mm for central features and 2.0 mm for right-hand features on the component. This assertion will be sufficient to demonstrate the component set-up logic, as shown in Fig. 7(b), employed by the combined feature MDA diagnosis of PADDES. The PADDES consultation results for the combined feature MDA diagnosis is as indicated in Fig. 9.

If a machine tool error is identified as a consequence of the combined feature MDA diagnosis activity the identified error is appended to the machine dependent historical log (.hlg) file. The historical log file for the Wadkin 4/6 vertical machining centre for the aforementioned machine out of calibration error identified by the combined feature analysis is depicted in Fig. 10.

The machine dependent historical log contains a detailed specification of the machine tool, obtained from the machine tool specification contained within the manufacturing model, and any machine tool dependent errors identified by the combined feature MDA diagnosis activity of PADDES. This file can be subsequently analysed to aid the production planner in both job routing and planned maintenance exercises.

## 6. Concluding discussions

This paper has presented and demonstrated that the novel application of prototype PADDES manufacturing data analysis expert system applied to the feature-based component manufacture provides a powerful prototype

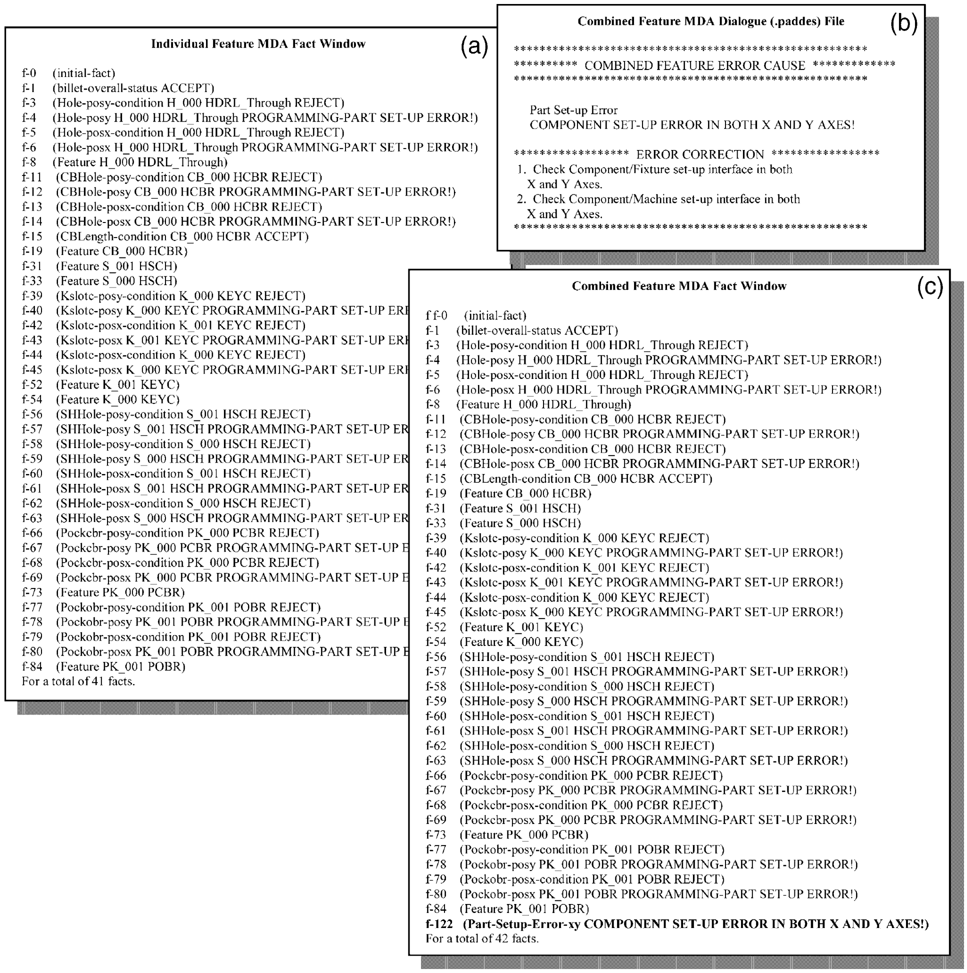



Fig. 9. PADDES consultation output of the combined feature analysis of the component set-up error in both the *X* and *Y* axes.

tool to diagnose manufacturing errors relating to machining, tooling, programming and set-up. This manufacturing data analysis capability, which forms the final analysis phase of a larger prototype PDA framework, provides feedback on manufacturing performance thus providing information to close the manufacturing feedback loop to support the day to day turbulent existence experienced by a typical metalworking SME. This prototype manufacturing data analysis expert system provides a valuable aid for the rapid diagnosis and elimination of manufacturing errors of milling, drilling, boring and reaming type operations on a 3-axis vertical machining centre in an environment where operator expertise is limited.

The authors acknowledge that this generic operation information is applicable for any type of milling process and as such can be applied to diagnose manufacturing errors produced on any type of three axis milling machine. To increase the knowledge of the PADDES diagnostic expert system to diagnose manufacturing errors for a particular milling machine, specific machine information must be acquired from an additional expert source. This additional machine dependent knowledge can be acquired through knowledge elicitation from an experienced operative or by the inclusion of condition monitoring data.

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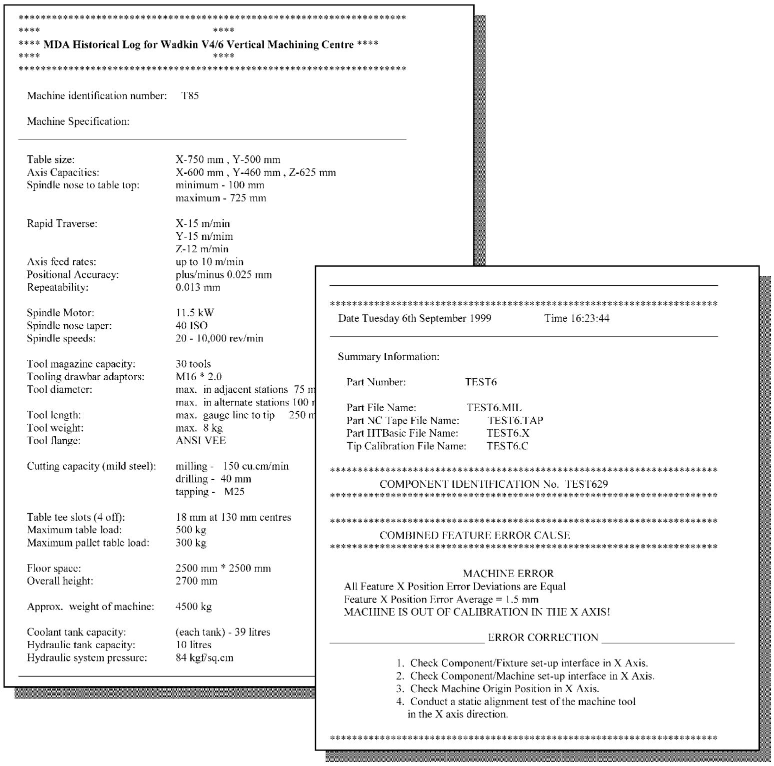


Fig. 10. The Wadkin 4/6 vertical machining centre's machine dependent historical log.

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