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Knowledge-based quality control in manufacturing processes with application to the automotive industry

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Geleitwort der Herausgeber
(Foreword)

Die Produktionstechnik ist für die Weiterentwicklung unserer Industriegesellschaft von zentraler Bedeutung, denn die Leistungsfähigkeit eines Industriebetriebes hängt entscheidend von den eingesetzten Produktionsmitteln, den angewandten Produktionsverfahren und der eingeführten Produktionsorganisation ab. Erst das optimale Zusammenspiel von Mensch, Organisation und Technik erlaubt es, alle Potentiale für den Unternehmenserfolg auszuschöpfen.

Um in dem Spannungsfeld Komplexität, Kosten, Zeit und Qualität bestehen zu können, müssen Produktionsstrukturen ständig neu überdacht und weiterentwickelt werden. Dabei ist es notwendig, die Komplexität von Produkten, Produktionsabläufen und -systemen einerseits zu verringern und andererseits besser zu beherrschen.

Ziel der Forschungsarbeiten des iwb ist die ständige Verbesserung von Produktentwicklungs- und Planungssystemen, von Herstellverfahren sowie von Produktionsanlagen. Betriebsorganisation, Produktions- und Arbeitsstrukturen sowie Systeme zur Auftragsabwicklung werden unter besonderer Berücksichtigung mitarbeiterorientierter Anforderungen entwickelt. Die dabei notwendige Steigerung des Automatisierungsgrades darf jedoch nicht zu einer Verfestigung arbeitsteiliger Strukturen führen. Fragen der optimalen Einbindung des Menschen in den Produktentstehungsprozess spielen deshalb eine sehr wichtige Rolle.

Die im Rahmen dieser Buchreihe erscheinenden Bände stammen thematisch aus den Forschungsbereichen des iwb. Diese reichen von der Entwicklung von Produktionssystemen über deren Planung bis hin zu den eingesetzten Technologien in den Bereichen Fertigung und Montage. Steuerung und Betrieb von Produktionssystemen, Qualitätssicherung, Verfügbarkeit und Autonomie sind Querschnittsthemen hierfür. In den iwb Forschungsberichten werden neue Ergebnisse und Erkenntnisse aus der praxisnahen Forschung des iwb veröffentlicht. Diese Buchreihe soll dazu beitragen, den Wissenstransfer zwischen dem Hochschulbereich und dem Anwender in der Praxis zu verbessern.

Gunther Reinhart *Michael Zäh*

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I am grateful to my family for constantly blessing me with their prayers in spite of the distance. I am indebted to my dear father for being an example of hard work and principled living, my mother for her wholehearted love and my brother for his support and care.

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Haitham Rashidy
July 2008

Contents

List of abbreviations

3D	Three-dimensional
AG	Aktiengesellschaft (Public company)
AI	Artificial intelligence
ARL	Average run length
AS	Assembly station
BEP	Break-even point
BIW	Body-in-white
BMW	Bayerische Motoren Werke Aktiengesellschaft
BP	Backpropagation
CAD	Computer-aided design
CAQ	Computer-aided quality techniques
CAx	Computer-aided methods
CMM	Coordinate measurement machine
CMMS	Computerized maintenance management systems
COQ	Cost of quality
DIN	Deutsches Institut für Normung (German Institute for Standardization)
e. g.	For example
EOL	End-of-line
EPC	Engineering process control
ES	Expert system
ETA	Event tree analysis
FEA	Finite element analysis
FMEA	Failure mode and effect analysis
FMS	Flexible measurement system
FOC	Fiber-optic cable
FTA	Fault tree analysis
GmbH	Gesellschaft mit begrenzter Haftung (Limited liability company)

GUI	Graphical user interface
i. e.	That is (Latin: id est)
Iff	If and only if
IP	Inner door panel
IPR	Inner panel reinforcement
IT	Information technology
KBS	Knowledge-based system
LSL	Lower specification limit
MFNN	Multilayer feedforward neural network
MIMO	Multiple input multiple output
MNN	Multi-neural network
MES	Management execution system
MP	Measurement point
MSE	Mean square error
NN	Neural network(s)
OCMM	Optical coordinate measurement machine
OEE	Overall equipment effectiveness
OEM	Original equipment manufacturer
OP	Outer panel
OPR	Outer panel reinforcement
PAF	Prevention-appraisal-failure
PCA	Principal component analysis
PDM	Product data management
PLC	Programmable logic controller
PLS	Partial least squares
PR	Pattern recognition
ProRID	Acronym of the developed software prototype: Process/ Recognition, Identification and Decision
QLF	Quality loss function
SCADA	Supervisory control and data acquisition
SOP	Start of production

SPC	Statistical process control
USL	Upper specification limit

List of symbols

Latin

A	-	Event of an alarm signal
aRPN	-	Adapted risk priority number
C	€	Cost
C_a	€	Quality loss
C_b	€	Cost of process adjustment
C_p, C_{pk}	-	Process capability indices
d	-	Mean shift in units of standard deviation
D	-	Fault detectability
D'	-	Adapted fault detectability, i. e. the analysis effort and time
$E(\cdot)$	-	Expected value
F	-	Event of a fault
k	€/mm^2	Constant
L	€	Loss
m	-	Process mean or target value, unitless or in mm
n	-	Number of … (e. g. samples, neurons, etc.)
O	-	Fault occurrence likelihood
O'	-	Adapted fault occurrence likelihood
$P(\cdot)$	-	Probability
q	-	Assignable cause variation
QC	mm	Quality characteristic
R_i	-	i^{th} if-then rule
RPN	-	Risk priority number
s	-	Slope of a trend in process mean
S	-	Fault severity
S'	-	Adapted fault severity, i. e. the impact of the root cause on the fault pattern
t	part	Discrete time as number of produced parts

T	part	Time interval expressed as a number of produced parts (e. g. maintenance cycle)
u	-	Factor determining presence of assignable cause variation
v	-	Common cause variation
VC dim	-	Vapnic-Chervonenkis dimension
x	-	Standardized value of a quality characteristic (sampled or simulated)
y	mm	Measurable variable related to the product or the process
z	-	Standardized form of a measurable variable related to the product or the process

Greek

α	-	Matching degree of a fuzzy rule
Δ	-	Deviation, unitless or in mm
μ	mm	Process mean or
	-	Membership degree in a fuzzy set
σ	mm	Standard deviation

List of figures

List of tables

1 Introduction

1.1 Quality and knowledge - The big picture

Quality as a success factor

Quality is a decisive success factor and one of the competitive edges of modern manufacturers. In many production scenarios, maintaining high product quality and production efficiency entails the extensive use of advanced process monitoring, control and adjustment techniques. In this regard, pertaining literature reports that quality related costs may run at 20-40% of sales [JURAN & GYRNA 1988, TAGUCHI et al. 1989]. In recent decades, researchers and international organizations stressed that the cost of quality is not the price of creating a quality product or service. It is the cost of not creating a quality product or service, hence, more intuitively known as the cost of poor quality [BESTERFIELD 1990].

Advanced process design and offline fault analysis methods do reduce failure risks [WHITNEY 1996]. But, offline methods alone are not enough since any process will drift if no control is applied [DEL CASTILLO 2002]. According to ROSS 1995, continuous adjustment, even within tolerance limits, is a must for more competitive products that bear minimized losses to the society. The premise that each failure has a root cause, causes are preventable, and prevention is cheaper [BESTERFIELD 1990] represents the underlying motivation for a number of research activities in the field of online quality control. Such research initiatives addressed process monitoring [ANAGUN 1998, BARGHASH & SANTARISI 2004], fault diagnosis and recovery [BALLÉ & FUESSEL 2000, BEN-GAL et al. 2003] and their integration [DEL CASTILLO 2002, GUH 2003] in order to deal with production disturbances, ranging from minor quality nonconformance to complete equipment failure.

In sharp contrast to research activities, a study of manufacturing priorities in the industrial and the consumer goods sectors (Figure 1.1) shows a rather paradoxical situation [A. T. KEARNEY 2005]. Increasing product quality and eliminating defectives are not on the top of the priority list when production costs are considered. The finding is alerting in the light of the impact of product quality on the overall performance and profitability. In spite of the current advances in quality engineering, this key function promises yet a greater profit potential in industrial practices if it is assigned more resources.

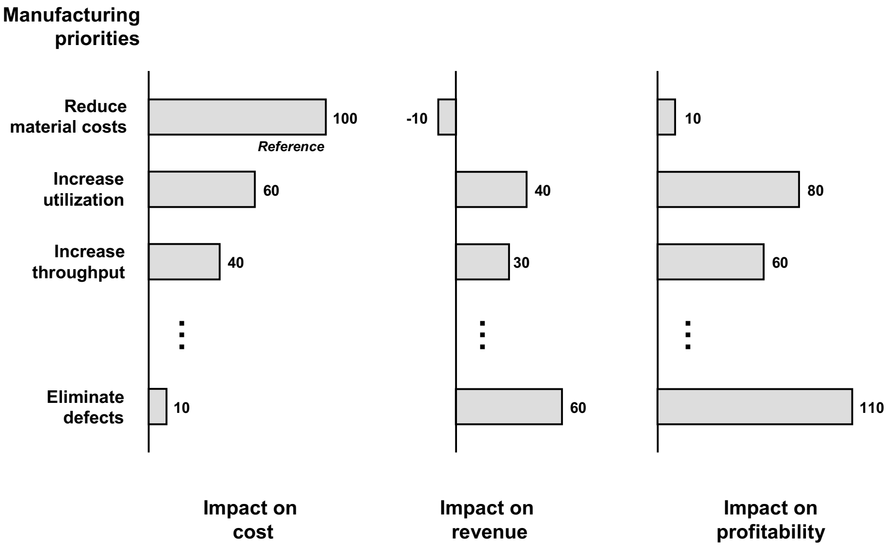

Figure 1.1: Impact of manufacturing priorities on cost, revenue and profitability [A. T. KEARNEY 2005]. All values are relative to the upper left entry marked as reference.

Quality as a shared responsibility

Quality, maintenance and operation personnel, often separate teams, cooperate to solve quality problems as quickly and as efficiently as possible. The know-how of the quality planning team complements the task. Such shared responsibilities and extensive experience involved in the fault recovery process have led to the development of computer-aided approaches (CAx) in the three areas to facilitate the interdisciplinary communication and to yield a more efficient production process.

The nature of quality problems

Generally, if complete failure or equipment stoppage occurs, e. g. due to crash, the fault cause is easy to identify and correct. Most original equipment manufacturers (OEM) have integrated standard diagnosis functions in their control software. Commercial product data management (PDM) systems offer further assistance in the monitoring and diagnosis of production machinery. The situation is different when dealing with quality problems of assembled products. In practice, manufacturers install quality inspection equipment in order to prevent defective products from reaching the customer. However, these systems have limited abilities as to fault identification, diagnosis, and recovery. Inferring a fault root cause or a recovery action based on the analysis of a product's deviation from target quality characteristics depends heavily on the experience and the know-how of the involved personnel.

Knowledge as a success factor

Knowledge is regarded as one of the most important issues affecting the success of individuals and organizations. The role of knowledge in the industry has been emphasized in recent years [OETZMANN 2005, RUDOLF 2007], as companies have become more aware of their dependence on qualified staff due to increasing market pressure. Knowledge preserving measures, such as knowledge and competence management policies or the implementation of expert knowledge-based applications, contribute to sustaining and reinforcing the competitiveness of a company [HANNULA et al. 2003]. The most valuable asset in knowledge-related practices is by far the human expert who represents the ultimate decision-making *machine*. Figure 1.2 shows a simplified view of data processing into knowledge.

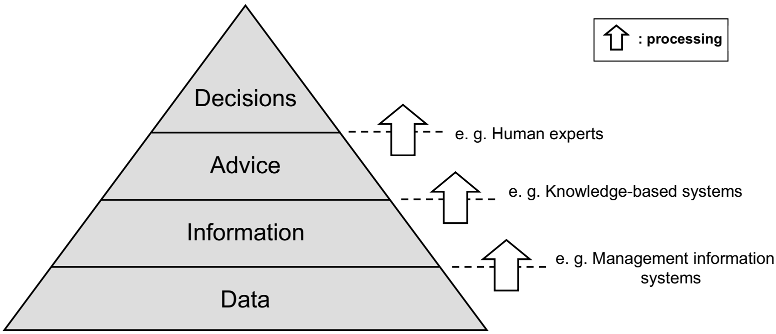

Figure 1.2: Volume versus value in data processing (after [HARRIS-JONES 1995])

1.2 Current situation in operative quality control

DEL CASTILLO 2002 summarizes the difference between quality control and traditional engineering process control (EPC) as given in Table 1.1. He suggests that these two apparently opposing viewpoints need to be reconciled and notes that the need exists for the increased application of EPC-based techniques for quality control.

Table 1.1: Process control versus quality control [DEL CASTILLO 2002]

	Process control	Quality control
Output(s)	Process variable(s)	Quality characteristic(s)
Input(s)	Process variable(s)	Process variable(s)
Control action	Automatic	Usually manual

Considering an arbitrary automated series production process, schematically represented in Figure 1.3, it can be said that the process control comprises two main tasks: data acquisition and control action. Acquisition of process and product data involves sensor technology, measurement principles and monitoring techniques. The control block handles aspects of data interpretation, reference process behavior, decision logic, and feedback of the control action.

Automated data acquisition has witnessed relatively more advances in recent decades than the automation of the control action. There are several reasons why automated inline inspection of product specifications has been applied: short reaction time, reduction of rework and scrap, reduction of logistic costs and high measurement capacity, to name a few. The basic disadvantage of inline measurement is the high initial cost. In addition, the accessibility of all needed quality criteria is not always guaranteed. Many applications allow equipment and process parameters to be monitored as well, such that alarms can be automatically signaled when unusual process conditions occur. However, this is highly process specific and is not always possible. For example, it is not feasible to automatically monitor the condition of fixtures in an assembly line.

Deducing the control action is more complex. Modern production processes pose challenging fault diagnosis tasks, which may entail costly scrap and lag until the fault is eliminated. Experience plays a significant role in assessing the fault severity; what a young engineer, by nature more conservative, considers as scrap might well be rework for a more experienced specialist. Moreover, in order to maintain a stable process, it is not only important to accumulate experience but to ensure its availability and accessibility also. A parallel factor adding to the difficulty of such diagnostic tasks is the often encountered lack of documentation since most manufacturers rely on short fault description in spreadsheet form. Noteworthy is that recent advances in PDM systems and computerized maintenance management systems (CMMS) have improved the situation. However, contrary to both acronyms, the focus on operative implementation, rather than on management, is still lagging. Specialized CAx tools for troubleshooting product quality problems and fault root cause analysis are a rare commodity in practical applications.

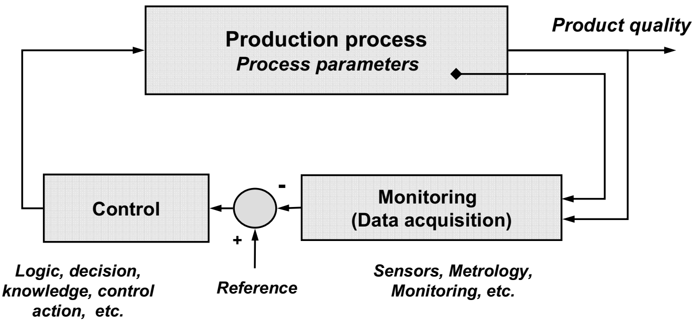

Figure 1.3. Control of a production process in a closed-loop representation

Among the different research directions initiated in response to the unsatisfactory situation was the implementation of model-based quality control techniques in analogy to conventional EPC paradigms [SACHS et al. 1995, DEL CASTILLO 2002, CARLSON & SÖDERBERG 2003]. Also, approaches rooted in the fields of artificial intelligence (AI) and knowledge engineering were used for the same purpose. Models for process stability analysis, fault diagnosis, decision support and corrective actions were successfully built in this way [CHANG & HO 1999, CHEN & HWANG 1992, CAIAZZO et al. 2004]. This thesis belongs to the latter category, and addresses the use of AI and knowledge-based systems (KBS) for quality control in automotive body-in-white production.

1.3 Problem definition

Body-in-white (BIW) production is a representative example of a class of complex automated manufacturing processes, where the aforementioned situation is witnessed. Figure 1.4 illustrates the result of a study conducted by CEGLAREK & SHI 1995 showing that maintenance problems dominate the production phase of the automotive body. Of the studied cases, 56% were related to subassemblies, 20% to framing and 2% to final assemblies. The remaining 22% were due to panel variations. The relations between the dimensional variation of the vehicle and its functional performance, as well as assembly line failures during production are not very clearly understood [HU 1997, CEGLAREK & SHI 1997, CARLSON & SÖDERBERG 2003]. As such, the process of fault elimination is highly subjective and vulnerable due to a number of factors that can be summarized as follows:

- Monitoring techniques, such as statistical process control (SPC), do not explain the root causes of defects [PAN 2002].
- The employment of pure engineering judgment brings an element of uncertainty to the decision making process.

- Regular employee rotations affect the level of available experience.
- Lacking fault documentation yields inefficient knowledge management.
- The link between planning and operation teams weakens after start of production (SOP).
- Fault handling is a shared responsibility between maintenance, quality and operation personnel, which adds organizational costs to the fault recovery process.
- The total losses due to fault diagnosis effort and time are often not fully quantified and the real costs of a fault are underestimated.
- The process stages are physically similar.
- It is difficult to predict product specifications since no accurate process models are available.
- Only end-of-line (EOL) measurements are possible.
- Monitoring all process parameters affecting the geometry, such as positions of fixtures, is not feasible.

BIW production in high-wage countries has developed into a nearly fully automated process with integrated inline quality monitoring solutions for 100% inspection, and, hence, is well suited for the application of online CAx tools. As detailed later in Chapter 3, a field study conducted at a German automotive manufacturer substantiated the necessity of exploiting further improvement potentials in the handling of quality problems (Figure 1.5).

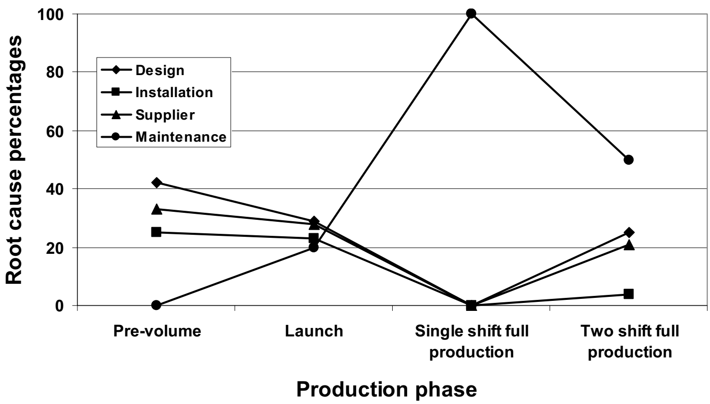

Figure 1.4: BIW dimensional fault root cause classification [CEGLAREK & SHI 1995]

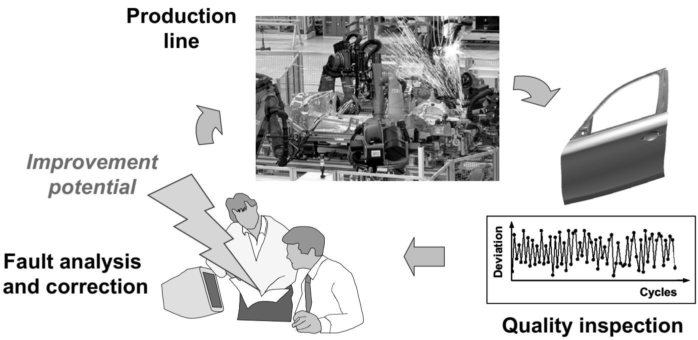

Figure 1.5: Current fault analysis procedures in BIW represent an improvement potential for the reduction of production costs

1.4 Objective and approach

Based on the previous discussion, the objective of this research can be formulated as:

> The development of a knowledge-based system (KBS) for fault diagnosis and decision support in online quality control of manufacturing processes with the example of body-in-white production

The KBS aims at aiding the human analyst with tools for quantitative knowledge representation that can be annexed to existing monitoring systems. The objective can also be seen as an attempt to realize semi-automated closed-loop handling of quality problems. The term *knowledge-based* is generally defined by *Knowledge-based Systems*[1] as follows.

"*Knowledge-based systems support human decision-making, learning and action. Such systems are capable of cooperating with human users and so the quality of support given and the manner of its presentation are important issues.*"

Throughout the thesis, the focus will remain on the automotive BIW production, as described in the problem definition. Data obtained from a field study and recommendations from the literature will be used to identify the solution requirements and to design a modular diagnostic system, with a fault knowledge base as its core compo-

[1] *Knowledge-Based Systems* is the international, interdisciplinary and application-oriented journal on KBS. <www.sciencedirect.com/science/journal/09507051>

nent. The three shaded blocks in Figure 1.6 represent the three basic tasks that will be investigated in the course of this research, which are:

- Fault recognition: the detection of abnormalities in the process
- Fault identification: associating an abnormality with a special cause
- Decision: applying or deferring a process adjustment

The scope of this research does not include the measurement system. Neither will the implementation of the corrective action be addressed in the sense of physical manipulation of the process parameters.

1.5 Thesis structure

This chapter presented an introduction to the research problem and the objective of the thesis. Chapter 2 reviews pertaining literature on process monitoring, fault diagnosis and related issues. Previous approaches to integrating fault knowledge databases in online control are also presented. Findings from a field study conducted at an automotive production facility are included in Chapter 3. Chapter 4 gives an overview of the architecture of the proposed diagnostic system. The development of the system components is described in Chapter 5, Chapter 6 and Chapter 7. Chapter 8 illustrates an exemplary application scenario and a software prototype of the integrated system. A technical and economical assessment of the system is given in Chapter 9. A summary and perspectives for further research can be found in Chapter 10. Table 1.2 gives an overview of the thesis.

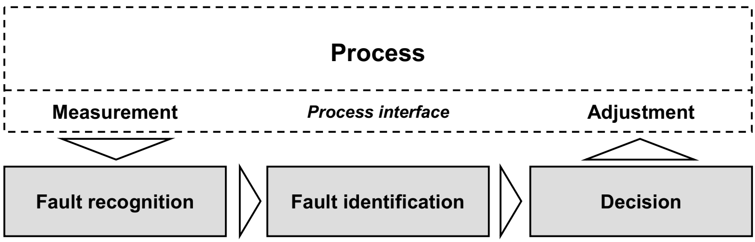

Figure 1.6: Basic tasks in the fault recovery loop

Table 1.2: Overview of the thesis

Chapter	Content
1	Introduction, problem definition and objective
2	Review of pertaining literature in order to establish the theoretical need for further KBS research in a quality control context
3	Field study showing the situation in a BIW production facility and establishing the practical need for alternatives in operative quality control
4	Overview of the proposed solution consisting of a modular structure of specialized submodels
5	Details of the fault recognition module responsible for triggering alarm signals in the case of quality deviations
6	Details of the fault identification module responsible for determining the fault root cause for the quality deviation and providing the user with troubleshooting instructions
7	Details of the decision module responsible for issuing a recommendation to the user in case immediate process interruption is required
8	Discussion of the system integration and a software prototype
9	Discussion of the impact of the proposed system on the overall performance of BIW production in technical and economical terms
10	Summary and future research directions

2 Literature review

2.1 Overview

The chapter reviews recent research activities pertaining to the issues of monitoring, diagnosis and control of manufacturing processes. The discussion is intended for applications in the areas of quality control and fault diagnosis. The onset of the chapter gives an overview of some definitions related to quality control, fault diagnosis and knowledge engineering. These definitions represent the larger context for understanding more specific issues detailed later in the thesis. The section titled process monitoring discusses the aspect of fault recognition in technical processes. A following section handles the fault identification task including modeling for diagnosis purposes as well as KBS design in process diagnostics. A third section introduces some exemplary diagnostic approaches that integrate decision support aspects and closed-loop approaches in quality control. Finally, the conclusion of the chapter summarizes important findings and trends in the surveyed literature.

2.2 Terms and definitions

2.2.1 Quality control and fault diagnosis

DIN EN ISO 9000:2005 defines quality as the degree to which a set of inherent characteristics fulfills requirements. Quality management is explained as the body of coordinated activities to direct and control an organization with respect to quality. Quality control is the part of quality management that is focused on fulfilling quality requirements. DIN EN ISO 9000:2005 also describes a process as a set of interrelated or interacting activities which transforms inputs into outputs. A product is thus the result of a process.

A product that exhibits quality nonconformity is a faulty product. This is explained by the definition of a fault as the state of an item characterized by the inability to perform a required function [DIN EN 13306:2001]. According to DIN EN 13306:2001, a *fault* is a state and is distinguished from *failure*, which is an event. Failure is defined as the termination of the ability of an item to perform a required function, i. e. a permanent interruption. A failure (or fault) cause is the reason leading to a failure (or fault). For the most part of the thesis, states are more relevant than events, and the term fault will be used more often in further discussions relating to quality defects or production disturbances.

A fault may also be defined as an unpermitted deviation of a characteristic(s) of an item or a system [ISERMANN & BALLÉ 1997]. Some publications, such as ABU-

HAMDAN & EL-GIZAWY 1997 and BAYDAR & SAITOU 2001, use the terms *error* and *fault* interchangeably in the context of assembly processes, which is confusing. ABU-HAMDAN & EL-GIZAWY 1997 define error propagation as carrying an undetected error from a previous task and coupling it with another error during a proceeding task. In BAYDAR & SAITOU 2001, the development of a fault pattern is described as an error propagation mechanism. Classically, the term error is more often used to describe deviations or uncertainties. Hence, the better practice is to adhere to the definition of error as the deviation between computed or measured values and their true or theoretical value [ISERMANN & BALLÉ 1997].

Inspection is a check for conformity by measuring, observing, testing or gauging the relevant characteristics of an item. Monitoring is a manual or automatic activity intended to observe the actual state of an item. It is distinguished from inspection in that it evaluates changes with time [DIN EN 13306:2001]. Fault diagnosis includes actions taken for fault recognition, fault localization, and cause identification [DIN EN 13306:2001]. Fault localization refers to the identification of the faulty item. A diagnostic model can be defined as a set of relations which link specific input variables – the symptoms – to specific output variables – the faults [SIMANI et al. 2003].

It is reported that the terminology in the field of fault diagnosis is not clearly defined [ISERMANN & BALLÉ 1997, SIMANI et al. 2003]. For example, quality defects or product faults arise due to root causes in the process. However, these root causes represent faults as well – process faults. The classification of fault diagnosis methods and techniques is similarly problematic. Most developments and applications of diagnostic systems rely on combinations of different methods. A sharp categorization of such hybrid approaches even to acknowledged standards is difficult and in many cases of little practical value [GUTMANN 2005].

The topics handled in the rest of the chapter will be categorized according to the two main tasks of fault diagnosis: fault recognition (Section 2.3) and fault identification (Section 2.4). The other sections discuss related issues such as process control, decision support and the human role. The presentation of the topics in this way is more suited to the rest of the thesis. The definitions given in Table 2.1 refer to the use of the corresponding terms in the scope of this thesis. The given terms conform to the standards stated above. However, no claim is made on the formality of the definitions at this point. The use of the term *fault identification* in this thesis combines the fault localization and the root cause identification tasks as given by DIN EN 13306:2001 and used in SIMANI et al. 2003. Finally, the use of the term *decision* refers to the differentiation between immediate and deferred corrective actions upon detecting a fault.

Table 2.1: Terms and definitions used in the thesis

Term	Definition
Fault	The instance of one or more quality characteristics exhibiting deviation from the specification, regardless of it being an incipient or an abrupt fault
Fault pattern	The description of the observed deviations in the quality characteristics in vector form
Fault (root) cause	The process parameter responsible for the quality deviation, such as a fixture or a robot
Fault recognition	The instance of detecting deviation in the monitored quality characteristics
Fault (root cause) identification	Establishing an association between a possible root cause and the observed fault pattern
Process	General term describing the manufacturing procedures. A process is usually multistage. The term may be used to describe a single stage or the application of a certain technology in the production cycle as well.
Decision	The decision whether to adjust the process immediately after fault recognition or to defer the corrective action to a later point

2.2.2 Knowledge-based systems

Knowledge, knowledge base and inference

Knowledge is a combination of experiences, values and contextual information that may be grouped into explicit and tacit knowledge [DAVENPORT & PRUSAK 1998]. It is the source of the expert's ability to perform. In a similar way, knowledge storage and representation is the heart of any expert system (ES) or KBS. It is the function of such systems to safestore expert knowledge, to retrieve knowledge from storage and to infer new knowledge when required [GONZALEZ & DANKEL 1993, HARRIS-JONES 1995, JACKSON 1999].

The components of knowledge [ROLSTON 1988] can be generally viewed as:

Facts: true statements relative to the subject domain (factual knowledge)

Procedural rules: invariant rules describing sequences and relations relative to the subject domain (procedural knowledge)

Heuristic rules: general rules or rules of thumb extracted from relevant experience suggesting actions, sequences and relations when invariant rules are not available (heuristic knowledge)

In an ES or KBS, the two basic components that act as knowledge *containers* are the knowledge base and the inference engine. In manufacturing processes, the stored knowledge is more domain-specific than expressive of generic expert behavior.

The knowledge base contains factual, procedural and heuristic knowledge. Factual and procedural knowledge are that knowledge of the task domain that is widely shared, typically found in textbooks or journals, and commonly agreed upon by those knowledgeable in the particular field. Heuristic knowledge is the less rigorous, more experiential, more judgmental knowledge of performance. In contrast to factual knowledge, heuristic knowledge is rarely discussed, and is largely individualistic. Thus, knowledge bases consist of some encoding of the domain of expertise for the system. This can be in the form of semantic nets, procedural representations, production rules or frames [GRIFFIN & LEWIS 1989].

The inference engine is the component with the ability to infer new knowledge from existing knowledge using predefined rules and, hence, respond to varying situations or inputs. In many cases, there is no sharp boundary between the two components and a clear differentiation is not necessary and sometimes not possible.

Knowledge engineering

Knowledge engineering (Figure 2.1) is the process of acquiring domain-specific knowledge and building it into the knowledge base. The knowledge engineer is the person who transforms the acquired knowledge in accordance with a knowledge representation convention [ROLSTON 1988]. Knowledge acquisition is not a well defined process and knowledge may vary from primitive to complex statements and relations [JACKSON 1999]. KASABOV 1998 describes four general approaches for knowledge representation: statistical methods, symbolic AI rule-based systems, fuzzy systems and neural networks (NN).

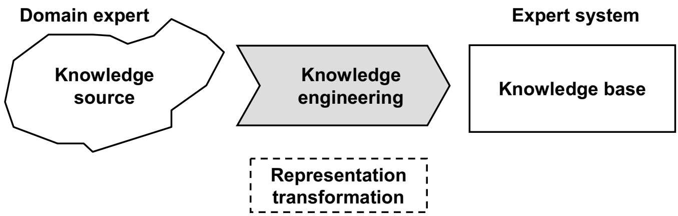

Figure 2.1: Role of knowledge engineering in ES design and maintenance

Expert systems

An ES is a computer program that represents and reasons with knowledge of some specialist subject with a view to solving problems or giving advice [JACKSON 1999]. ES derive originally from the research discipline of AI and are used to perform a variety of complicated tasks otherwise performed by highly trained human experts [ROLSTON 1988]. The general architecture of an ES is given in Figure 2.2. An ES is distinguished from conventional applications in that it simulates human reasoning and is capable of storing and retrieving specific knowledge and inferences. Furthermore, it solves problems by heuristics and approximate models. An ES also differs from other AI applications in its capability to deal with problems of realistic complexity that normally require a considerable amount of human expertise [JACKSON 1999].

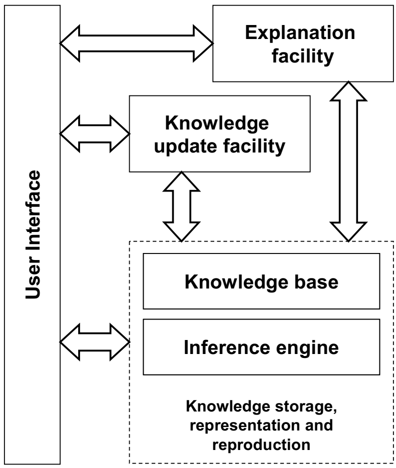

Figure 2.2: Typical ES architecture (after [ROLSTON 1988])

Knowledge-based systems

Very often, KBS and AI are mistakenly assumed to be one and the same [GONZALEZ & DANKEL 1993]. KBS emerged in the 1960s and 1970s as a new branch of AI research (Figure 2.3). It is the branch of AI which has, by far, seen the most success in terms of practical implantation. KBS is also sometimes used as a synonym for ES. However, strictly speaking the former is more general [JACKSON 1999, COUNCIL FOR SCIENCE AND SOCIETY 1989]. A vast number of definitions exist for KBS that have developed and changed through the last decades. One recent general definition of KBS is "*any system that performs a task by applying rules of thumb to a symbolic represen-*

tation of knowledge, instead of mostly algorithmic and mathematical methods [JACKSON 1999].” GONZALEZ & DANKEL 1993 suggest that a general KBS architecture would consist only of the knowledge base and the inference engine. Figure 2.4 lists general advantages and disadvantages of KBS.

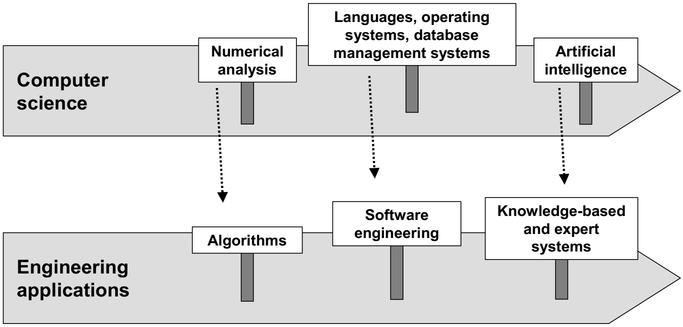

Figure 2.3: Developments in computer science and their corresponding engineering applications according to DYM & LEVITT 1991

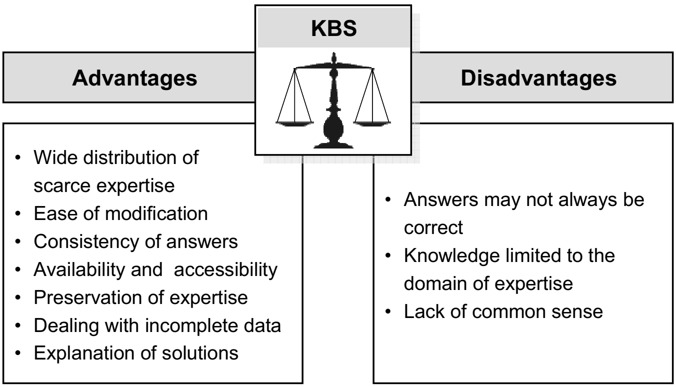

Figure 2.4: Advantages and disadvantages of KBS [GONZALEZ & DANKEL 1993]

KBS design procedures

The search for a common design methodology for KBS was the concern of many research activities in the past decades. Examples include KADS[2] and CommonKADS, which probably represent the most widely acknowledged knowledge engineering methodology [BORN 1990, SCHREIBER et al. 1994, KINGSTON 1998]. KADS proposes several diagram-based models which reflect knowledge from different perspectives and at different levels of abstraction as a supporting tool to the knowledge engineer [KINGSTON 1998]. MOKA[3] represents another example of structured knowledge engineering approaches [BERNARD et al. 2007]. Both KADS and MOKA provide frameworks for representing and for storing knowledge.

Nevertheless, in industrial applications, knowledge-based diagnosis of technical systems still depends mainly on tailored structures. The use of KBS design methodologies finds more interest among computer science and programming specialists rather than among process and industrial engineers.

2.3 Process monitoring

2.3.1 Introduction

The purpose of monitoring in a production facility is to ensure an optimal and steady status of the product and the equipment. Deviations between the desired and the actual states of the equipment or the quality of the product are formally known as residuals [SIMANI et al. 2003]. The fault diagnosis problem thus consists of two steps: residual generation and residual evaluation [BASSEVILLE 2003]. The residual should ideally be zero in normal operation conditions. In the BIW dimensional inspection, the residual would be the difference between the measured values of the quality characteristics and their specified target values. Different residual generation methods are discussed in the literature [ISERMANN 1984, ISERMANN & BALLÉ 1997, SIMANI et al. 2003]. Residual evaluation starts by the examination of symptoms in order to determine if a change in the operating conditions has occurred. The term fault recognition is widely used to describe this step since the aim is to recognize abnormalities in process behavior.

Another related term that evolved with the rise of machine learning and AI research is pattern recognition (PR). PR encompasses a wide range of information processing problems, from speech recognition and image analysis to fault detection in machinery and medical diagnosis [BISHOP 1995]. Such tasks may seem trivial to the human mind, but they pose a considerable challenge to modern computers. PR methods include fea-

[2] Knowledge-based Systems Analysis and Design Support

[3] Methodology and Tools Oriented to Knowledge Engineering Applications

ture extraction, error estimation, cluster analysis and statistical PR. Intelligent PR methods have found increasing application in the field of fault recognition in industrial environments [BONISSONE et al. 1999]. Their strengths show in the ability to detect incipient faults efficiently and their intuitive architectures. It is generally agreed that a well-defined and sufficiently constrained recognition problem will lead to a compact pattern representation and a simple decision making strategy [JAIN et al. 2000].

In the context of quality inspection and control, SPC is probably the most widely used tool for residual generation and change detection. Recent developments in monitoring strategies have led to increased integration of PR techniques into well established SPC schemes. The development is usually referred to as control chart PR [GUH & TANNOCK 1999a, JAIN et al. 2000]. The purpose of the integration is to enhance the ability of control charts in detecting out-of-control situations and recognizing patterns of incipient faults.

2.3.2 Statistical process control

The control chart was first proposed in 1924 by Shewhart with a view to eliminating abnormal variation by distinguishing variations due to assignable causes from common cause variation [KUME 1985]. Since then, different types of control charts have been developed for various applications [KUME 1985, JURAN & GYRNA 1988, DIETRICH & SCHULZE 1999, WOODALL 2000]. The ability to separate out special disturbances (out-of-control data) from inherent variability (in-control data) makes control charts a powerful tool for SPC applications [GUH & TANNOCK 1999b]. However, even when the process is deemed to be out-of-control, no adjustment strategies are explicitly specified in the SPC literature [PAN & DEL CASTILLO 2001]. SPC emphasizes monitoring a process and assessing whether or not the process has changed. Hence, the scope of SPC needs to be broadened to include an understanding of the manufacturing process [WOODALL 2000]. This will require more sophisticated modeling and the incorporation of more engineering knowledge of the process under study.

A simpler form of control charting is known as precontrol [STEINER 1997]. Precontrol does not define control limits as in a traditional control chart. The method is based on the specification limits, the range of which is divided into four parts of equal length. The middle two parts comprise the *green zone*. The outer two parts within the specification limits comprise the *yellow zones* and the region outside the specification limits corresponds to the *red zone*. Although it is not a generally valid substitute for control charts, LEDOLTER & SWERSEY 1997 identify specific situations in which precontrol has value. In industrial applications, precontrol is often favored for practical reasons, such as the ease of implementation, absence of assumptions, and reported success. The trend towards 100% quality inspection also led to increased use of precontrol. To the same end, techniques combining precontrol with conventional control charts have been introduced [STEINER 1997, PAN 2007].

Frequently, manufactured items need the values of several different quality characteristics for an adequate description of their quality [MARTIN et al. 1999]. Univariate charts do not take the presence of functional relationships between the variables into account and are often implemented together with correlation coefficients [JURAN & GYRNA 1988]. If the measured characteristics are not equally important or if they are correlated, multivariate SPC may be more sensitive to changes [OGAJA et al. 2002].

The beginning of multivariate SPC is marked by the work of Hotelling in 1947 [HOTELLING 1947]. Hotelling recognized that the quality of a product may depend on several correlated characteristics [NIAKI & ABBASI 2005]. He introduced a scalar statistic, appropriately named Hotelling's T^2, that combines information from the variance and mean of several variables. Later, the implementation of linear regression analysis, principal component analysis (PCA) and partial least squares (PLS) algorithms were proven successful for multivariate monitoring [ALT 1984, JACKSON 1985, KRESTA et al. 1991, NORVILAS et al. 2000, YIN et al. 2002]. ADAMS 1994 introduced a graphical approach to the display, interpretation and construction of multivariate control charts. PAN 2007 studies the combination between multivariate analysis and precontrol charts.

Multivariate charts tend to compress the available data streams and render the interpretation of the out-of-control situation difficult [ALT 1984, JACKSON 1985]. They do not possess fault signature properties for diagnosis [YIN et al. 2002]. Fault diagnosis based on multivariate charts is feasible if the charted multivariate quantity has physical significance [GOULDING et al. 2000]. This problem often discourages practitioners from applying these techniques. Also, most multivariate quality control procedures are not optimal for shifts that occur in a subset of the process variables [NIAKI & ABBASI 2005]. The use of both univariate and multivariate analyses is often the best, if not the only, way to guarantee effective diagnosis of process faults [LOWRY & MONTGOMERY 1995]. Subsequent diagnosis and root cause identification can be implemented by statistical methods such as clustering, by means of KBS, or by correlation models determining the process variables that have contributed to the fault and using this information with process knowledge to diagnose the fault [NORVILAS et al. 2000].

2.3.3 Fault pattern recognition for SPC

In SPC monitoring schemes of single characteristics, the use of run tests, also known as zone tests [KUME 1985, JURAN & GYRNA 1988], is a widely accepted technique for the recognition of abnormal process behavior. Since operating within the specification limits does not necessarily signify a stable process, these rules were devised for out-of-control situations regardless of operating within or beyond the specification limits.

Run tests have proven effective in indicating out-of-control situations. Their effectiveness in interpreting process data is, however, disputed. The major difficulty lies in the fact that there is no one-to-one mapping between a supplementary rule and an unnatural pattern [CHENG 1995]. Unnatural patterns may include shifts in process mean, trends, systematic variations, cycles and mixtures of these patterns (Figure 2.5). Also, if a large number of rules is implemented, the result would be an excessive number of false alarms without a breach of process control limits. Random noise might contaminate the present pattern. Moreover, patterns may sometimes exhibit resemblances. For instance, a short trend may be misinterpreted as a shift or vice versa.

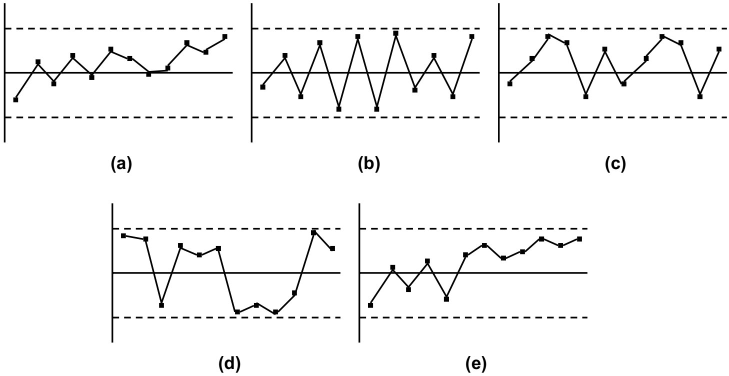

Figure 2.5: Examples of unnatural patterns (a) trend, (b) systematic variation, (c) cyclic, (d) mixture, (e) sudden shifts [GRANT & LEVENWORTH 1988]

As such, the analysis of a control chart becomes a PR problem [MONTGOMERY & KEATS 1994], i. e. recognizing systematic or unnatural patterns on the control chart. Consequently, more recent literature shows an increasing trend towards applying PR techniques for diagnostic purposes in the SPC context.

The best known approaches in PR are: template matching, statistical classification, syntactic or structural matching and NN [JAIN et al. 2000]. Template matching is rather rigid and would fail if the pattern is distorted or noisy. In syntactic matching, a pattern is regarded as a hierarchical structure of simpler sub-patterns. The application of syntactic matching is often associated with difficulties in the segmentation of noisy patterns, i. e. defining the basic blocks in the pattern hierarchical structure. NN and statistical PR methods are for most reported applications implicitly equivalent [FUKUNAGA 1990, ANDERSON et al. 1990, RIPLEY 1993, BISHOP 1995]. JAIN et al. 2000 state that NN offer several advantages such as, unified approaches for feature extraction and classification flexible procedures for finding good, moderately nonlinear solutions. The next section discusses NN applications for process monitoring.

2.3.4 Neural networks for process monitoring

A NN is a biologically inspired computational model that consists of parallel processing elements called neurons and connections between them, as well as of training and recall algorithms. NN are noise tolerant and learn by examples. In PR applications, they offer the ability to model nonlinearities and they require minimal a priori knowledge or model assumptions, besides being adaptive, stable and robust in nature [BISHOP 1995, SIMPSON 1990]. The generalization ability of NN is considered to be their foremost merit [VELASCO & ROWE 1993]. Generalization refers to the NN producing reasonable outputs for inputs not encountered during training. A thorough overview of NN classifications can be found in BISHOP 1995, KASABOV 1998 and HAYKIN 1999.

NN have been applied to SPC since the late 1980s. The basic motivation of that trend was the attempt to automate SPC chart interpretation. The application of NN to SPC has largely focused on univariate control charts [LARPKIATTAWORN 2003]. Several researchers have investigated the performance of NN in PR compared to that of traditional control charts. Mostly, the focus lay on the development of PR systems for univariate quality control charts. Applications in the literature handle the detection of deviations in mean and/or variance [CHENG 1995, WANG & CHEN 2002] and the identification of deviation patterns (unnatural patterns) on control charts [PHAM & OZTEMEL 1994a, GUH 2004].

Under the assumption of independence of the monitored characteristics, NN were proven to be an effective approach to control chart PR [HWARNG & HUBELE 1993, PHAM & OZTEMEL 1994a, PHAM & OZTEMEL 1994b, CHENG 1995, GUH & HSIEH 1999, GUH & TANNOCK 1999a, GUH 2004, NIAKI & ABBASI 2005]. For example, CHENG 1995 developed an NN-based control chart recognizer for mean shifts and trends that outperformed Shewhart charts in detecting moderate process changes up to 3σ. COOK & CHIU 1998 demonstrated the ability of NN to accurately identify step shifts in magnitude of 1.5σ to 2σ away from the mean. GUH & HSIEH 1999 and GUH & TANNOCK 1999a discuss the identification of pattern parameters, such as shift magnitudes and trend slopes. The information may be important for fault diagnosis in some applications.

In multivariate applications, NN models can be a powerful tool for addressing correlated manufacturing processes. Radial basis functions were applied to PLS [ADAMS 1994] and to PCA [WILSON & IRWIN 1998] for nonlinearly correlated data. VAN BRACKLE & REYNOLDS 1997 describe cases where multivariate control charts could not deliver acceptable performance. Examples where NN outperform conventional and time series control charts are found in the literature [COOK et al. 2001, CHIU et al. 2001, NOOROSSANA et al. 2003, ZOBEL et al. 2004]. Generally, however, fewer NN applications in multivariate SPC are reported as compared to univariate approaches [MYERS 1990, LARPKIATTAWORN 2003].

The cited applications show that intelligent PR techniques, especially NN, have outperformed conventional statistical classification methods. These techniques offer favorable advantages for modeling complex data interdependencies and are a suitable platform for integrated univariate and multivariate analysis of product data. The leverage of NN is basically due to two major aspects. The first is their ability to detect correlations between subsets of the input signals, which is a problem that received the attention of many researchers [KRESTA et al. 1991, CHIU et al. 2001, COOK et al. 2001, LARPKIATTAWORN 2003, NOOROSSANA et al. 2003]. The second aspect is the ability to model nonlinear relations between the monitored quality characteristics [WILSON & IRWIN 1998, GUH & HSIEH 1999, LARPKIATTAWORN 2003]. Up to date, manufacturers tend to apply single characteristic charts and linear correlation coefficients, thus failing to benefit from the capabilities of more advanced approaches.

The disadvantages of NN in process monitoring can be summarized in three points. It is nearly always necessary to preprocess the data so that only meaningful parameters are presented to the network [ANGELI & CHATZINIKOLAOU 2004]. The purpose of the preprocessing stage is to minimize the noise and maximize the accuracy of the NN computational model. The second limitation compared to other modeling approaches is their inability to explain the reasoning since they operate as black boxes using unknown rules. The third key constraint is the real time execution of neural techniques [KRAMER & FJELLHEIM 1996, BISHOP 1995].

The most important factors affecting the performance of NN in PR of unnatural process behavior are summarized in Table 2.2 [ZORRIASSATINE & TANNOCK 1998]. These factors are explained in Chapter 5.

Table 2.2: Factors affecting NN performance in control chart PR

Model structure	**Training procedure**
▪ Neural network paradigm ▪ Type of connection ▪ Number of hidden layers ▪ Number of neurons ▪ Activation function	▪ Data preprocessing ▪ Number of training patterns ▪ Frequency of training cycles ▪ Order of training patterns

2.4 Model-based diagnostic systems

2.4.1 Introduction

According to ASKIN & STANDRIDGE 1993, model building is an art. Science comes into play more in the model solution than in the building. The process of model building iterates between inductive and deductive reasoning. Induction involves deciding on the basic system aspects and assumptions using experience and intuition. Deductive reasoning describes the identified system components and relationships mathematically or logically.

SIMANI et al. 2003 consider fault identification the most important of all fault diagnosis tasks and note that it has not gained enough research attention. The core component of the diagnostic approach responsible for identification is a model of the considered process that may vary from a simple function to a complex multistage or hybrid model. The majority of all industrial processes is nonlinear in nature and cannot be captured by a single model for all operating conditions. However, most of the existing observer-based fault diagnosis schemes are limited to the use of linear models [PATTON et al. 2000b]. Worth noting is that most related literature in this field comes from the process industry [PERNE & ENDESFELDER 1999].

Several classification attempts of diagnosis systems are reported in the literature. SIMANI et al. 2003 differentiate between detection and isolation methods and describe fuzzy and neural methods as fault diagnosis technique integration. ANGELI & CHATZINIKOLAOU 2004 categorize fault diagnosis approaches into numerical, AI-based and combinations of both. VDI 2888 (1999-12) classifies diagnostic approaches into functional, model-based and knowledge-based. Considering published surveys [ISERMANN 1984, FRANK 1990, ISERMANN & BALLÉ 1997, SIMANI et al. 2003], there is no unique classification of diagnosis techniques. For the purpose of this thesis, it is enough to differentiate between quantitative and qualitative approaches in fault models, with more focus on the latter.

Quantitative approaches in fault diagnosis are basically signal processing techniques employing state and parameter estimation, variable threshold logic, statistical decision theory and analytical redundancy methods [ANGELI & CHATZINIKOLAOU 2004]. Applications relying on analytical redundancy methods are termed quantitative model-based methods [PATTON & CHEN 1992]. The former approaches are collectively known as numerical or functional approaches. BASSEVILLE 2003 presents a good survey of model-based approaches to fault diagnosis with a focus on linear models of dynamic systems. Several other applications of quantitative model-based diagnosis are reported in [FRANK 1990, FERREIRO GARCÍA et al. 1999, SIMANI et al. 2003, GUTMANN 2005]. The second category of diagnostic techniques includes applications involving qualitative knowledge.

2.4.2 Model-based diagnosis with qualitative knowledge

Where valid mathematical models do not exist or access to process variables is limited, a number of different methods have been proposed that rely on symbolic, logical or linguistic descriptions of system behavior. Such qualitative model-based approaches often involve the use of soft computing methods. Soft computing stands for all methods employing computational intelligence algorithms [BONISSONE et al. 1999, PATTON et al. 2000b, GOEBEL 2006], e. g. fuzzy logic [DEXTER & BENOUARETS 1997, RAUMA 1997], NN [AYOUBI 1995, MADANI 1999], neuro-fuzzy schemes [ZHANG & MORRIS 1994, RASHIDY et al. 2003] and evolutionary programming [GRASSO et al. 2004, LO et al. 2007]. Qualitative approaches in online fault diagnosis offer the advantage of avoiding time consuming mathematical modeling [MÉSZÁROS & ROMAN 1997]. But, they only offer solutions in cases where highly accurate numerical knowledge is not needed.

Many of the reported applications have a hybrid character, where two or more methods are combined to yield a more effective diagnosis system. KUO & HUANG 2000 combine SPC, Petri nets and fault trees for failure modeling of a flexible manufacturing system. MANDERS 2003 developed a combined statistical detection and qualitative fault isolation for identifying abrupt faults in dynamic systems. ZHANG & MORRIS 1994 propose a fuzzy-neural diagnostic system architecture and apply it to a continuous stirred tank reactor. BAYDAR & SAITOU 2001 present a qualitative approach to detecting and diagnosing faults in processes where monitoring of production parameters is infeasible. MÉSZÁROS & ROMAN 1997 investigate the differences between analytical and empirical approaches to qualitative modeling from a computer science viewpoint. BALLÉ & FUESSEL 2000, LAKHMI & MARTIN 1998, MATHUR et al. 2001 and LO et al. 2007 present examples for similar qualitative applications.

Knowledge-based diagnosis falls under qualitative approaches [ANGELI & CHATZINIKOLAOU 2004], where the diagnostic system contains a knowledge base and an inference engine as defined in Section 2.2.2.

2.4.3 Knowledge-based diagnostic systems

In his survey of fault diagnosis techniques in dynamic systems, FRANK 1990 states that "*Logically, there is some potential in using knowledge-based models instead of analytical models. This is the only way of FDI*[4] *in all such cases where analytical models are not available. Therefore, the knowledge-based approach may be looked upon as an alternative to the analytical model-based approach, or may complement it.*"

[4] Fault detection and isolation

The KBS paradigm in fault diagnosis often combines quantitative and qualitative methods. This combination allows the evaluation of all available information and knowledge about the considered process [GUIDA & STEFANINI 1992]. According to SIMANI et al. 2003, "*a comprehensive approach to fault diagnosis should exploit a knowledge-based treatment of all available analytical and heuristic information*."

Recalling the definition of ASKIN & STANDRIDGE 1993 of a model (refer to the previous section), a knowledge base can be considered a model. In the case of automotive BIW dimensional control, a diagnostic knowledge base would be a model relating certain process instability patterns to their possible root causes.

Practical needs in the field of diagnosis and process control have accelerated KBS research. Since the early eighties, the manufacturing sector has witnessed considerable investments in diagnostic techniques in general, with a traceable trend towards knowledge-based techniques [GUIDA & STEFANINI 1992]. The reason is that these techniques use association, reasoning and decision-making processes as would the human brain in solving diagnostic problems. Classical fault detection methods are based on limit value checking of important measurable variables, do not allow in-depth fault diagnosis and do not simulate human reasoning [ANGELI & CHATZINIKOLAOU 2004].

MYCIN was the first rule-based system developed to diagnose bacterial blood diseases in the early 1970s [SHORTLIFFE 1976]. RIEDESEL 1989 discussed the issue of quantitative versus qualitative modeling and the problems inherent to diagnosing multiple faults. PRASAD & DAVIS 1993 describe a conceptual framework for knowledge-based fault diagnosis in chemical plants. The framework combines predefined information processing tasks [CHANDRASEKARAN 1989] that may be knowledge-based or numeric in nature. LARSSON 2002 proposes the use of the means-end approach to fault diagnosis of a nuclear plant. CUNNINGHAM et al. 1998 present an incremental retrieval mechanism for case-based electronic fault diagnosis. RAUMA 1997 discusses the implementation of diagnosis information as meta-rule adaptive fuzzy systems.

WAGNER 1997 integrated a fault diagnosis system in the control architecture of a CNC milling machine. His system relied on a combination of statistical analysis of PLC data and a specific-purpose NN. A signal-based quality control loop for technical diagnosis is presented in RITSCHEL 1996. The proposed diagnostic approach combines symbolic and subsymbolic knowledge representation and is applied to a frequency domain problem. PATEL et al. 1995 introduced an offline diagnostic application for robotic systems. His approach permits the diagnostic application to be interfaced to a maintenance management system. He concluded that, although robots possess more robust structures, the increased complexity renders it difficult to correctly diagnose the failure of robotic systems, especially for a non-expert.

GUTMANN 2005 presented a knowledge-based diagnosis system for hydraulic machines incorporating fuzzy inference. In VON EULER-CHELPIN et al. 2006, a model was presented for capturing operational knowledge of machining resources with interfaces to theoretical manufacturing system models. An if-then structure for the production knowledge was implemented that considers measured parameters, events and runtime experiences. Better feedback opportunities of runtime information could be achieved through the approach. An application in the process industry is reported in KRÜGER et al. 2005 where knowledge modeling for supervision of process facilities is discussed.

The observation of recent developments in KBS design shows increased tendency towards hybrid approaches in order to produce more effective tools for early and reliable fault diagnosis [ISERMANN 1984, ISERMANN & BALLÉ 1997, ANGELI & CHATZINIKOLAOU 2004]. For FRANK 1990, such hybrid techniques open a new dimension on fault diagnosis for complex processes with incomplete process knowledge. Figure 2.6 illustrates a possible architecture of a combined analytical model-based and knowledge-based real-time diagnosis system.

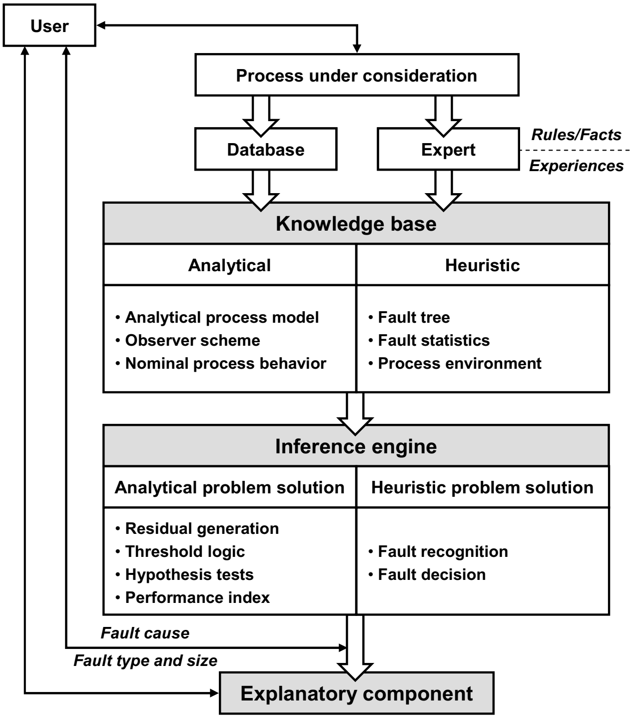

Figure 2.6: Architecture of a combined analytical model-based and knowledge-based real-time diagnosis system [FRANK 1990]

Although numerous diagnostic KBS applications were developed since their advent, it is noted that relatively few research works addressed real industrial needs such as the integration of diagnosis and maintenance [MILACIC & MAJSTOROVIC 1987, PATEL et al. 1995, JACKSON 1999]. This may be attributed to the fact that not all fault models are suited for online implementation due to lacking integration of analytical and qualitative knowledge. Also, for some applications, the required online data acquisition and sensor scheme may be too expensive. Further KBS applications are listed in published survey papers [ISERMANN 1984, XU & LILIEN 1987, RIEDESEL 1989, FRANK 1990, ISERMANN & BALLÉ 1997, PATTON et al. 2000a, PATTON et al. 2000b, ANGELI & CHATZINIKOLAOU 2004, STEINDERA & SETHIB 2004].

2.4.4 Modeling and diagnosis in body-in-white assembly

Basically driven by the automotive industry, variation simulation and tolerance analysis for assembly has witnessed accelerated progress [DANIEL et al. 1986, JIN & SHI 1999]. Most of the early work conducted in this field follows a form closure approach that considers the kinematic relations between component dimensions. However, during assembly, component dimensions can change due to clamping and welding forces. TAKEZAWA 1980 formally declared that conventional tolerance stackup is not valid for automotive body assembly and advocated the application of force closure models. While in Europe and Japan, the focus lay on the weld technology and its impact on the build process, much work was conducted in North America on variation propagation models in multistage manufacturing processes, especially in automotive BIW [HU 1997, CEGLAREK et al. 2001, DING et al. 2004, DING et al. 2005]. Among the approaches often used for fixture modeling were screw theory and force equilibrium equations [JIN & SHI 1999].

The stream-of-variation theory was introduced for predicting variation in multi-leveled manufacturing systems [CEGLAREK & SHI 1995, CEGLAREK & SHI 1997, HU 1997]. However, explicit variation models are too complex and impractical. For this reason, the use of finite element analysis (FEA) in combination with statistical methods was suggested in order to generate accurate models [HU 1997]. A comparison of several variation estimators is given in DING et al. 2004. For ill-conditioned assemblies, RONG et al. 2001 propose a modified least square approach. Finite element and influence coefficient methods are implemented to determine the sensitivity matrix in the case study described in CAMELIO et al. 2004. DING et al. 2005 investigated the combination of product and process variables in the tolerance analysis. CHASE et al. 1996 combined models of geometric and dimensional variation in tolerance analysis of mechanical assemblies. DING et al. 2002a compared different system level variation models. CEGLAREK et al. 2001, VON PRAUN 2003 and LUSTIG et al. 2005 addressed tolerancing of non-rigid sheet metal parts. VON PRAUN 2003 differentiates between attributive and mathematical representation of geometric variation. Attributive methods, such as data-driven models or object-oriented models, allow processing tolerance information using a combination of computer-aided design (CAD) systems and stand-alone tolerance management software.

Only a few of the described tolerance models are suitable for diagnostic purposes. For BIW diagnosis, only EOL measurements are available, i. e. the only available information is the fault pattern. Practically, any mathematical analysis in this case would lead to a number of possible fault root causes. It is helpful in such cases to consider additional factors such as fault severity, fault probability and previous experience in the diagnosis procedure.

Generally, few attempts were made to develop fault diagnosis applications in BIW assembly as an extension to the dimensional control process. These efforts are mostly concentrated in North American universities and often associated with the state space approach. For example, the variation model developed by JIN & SHI 1999 was implemented by DING et al. 2002b for the diagnosis of faults in automotive assembly. Other applications include the use of statistical description of variation [JIN & SHI 1999], PCA [TSUNG 1999] and hypothesis analysis [ZHOU et al. 2004]. CARLSON & SÖDERBERG 2003 implemented numerical approximations to determine locator errors in assembly operations. All these models are of analytical nature that aimed at simulating possible fault scenarios in the assembly process. The predefined faults and the resulting patterns are thus affected by the quality of the model and the modeling assumptions.

Besides the quantitative approaches, a few examples implementing qualitative knowledge were reported. A rule-based diagnosis system for sheet metal assembly was introduced in BAYDAR & SAITOU 2001. An attempt for implementing KBS in fault diagnosis of BIW assembly is described in CEGLAREK et al. 1994, where knowledge gained in the design stage of the automotive body was used for fault diagnosis during the launch phase of the BIW assembly line. Contrary to the viewpoint of SIMANI et al. 2003 stressing the benefits of integrating heuristics in knowledge-based diagnosis, CEGLAREK et al. 1994 implement a pure analytical approach.

2.5 Integration of diagnosis, decision support and process control

2.5.1 Introduction

The use of closed-loop strategies in handling quality problems is advantageous for the overall process economics [BLEY et al. 2005]. Process control infrastructure can easily be extended to accommodate automated diagnosis algorithms, especially those rooted in AI. The need for such a development was acknowledged by many researchers in order to cope with more stringent product specifications [DEL CASTILLO 2002]. The control architecture of modern processes should be able to react not only in well-defined situations, but also to unexpected changes in conditions. One major area of promising benefits is that of advisory systems for early fault recognition and identification. Fault diagnosis is thus an extension of control that leads to control actions in response to faults and can be viewed as a decision-making activity of qualitative nature [PRASAD & DAVIS 1993].

Two issues are addressed next: process control and decision support. The discussion serves as an overview of methods and considerations that are necessary for conducting a corrective action. The approaches presented next do not explicitly handle the action execution aspect. They rather concentrate on defining the corrective action. The scope of decision support is restricted to two major considerations in the context of quality control: the fault identification certainty and the overall process economics. Finally, the human decision-making process as a source of error is briefly discussed.

2.5.2 Process control

2.5.2.1 Fault-adaptive control

Fault-adaptive control or fault-tolerant control involves solving a number of technical problems beyond the capabilities of traditional control approaches [KARSAI et al. 2003]. In addition to the control algorithm, faults must be detected, nominal behavior of the plant must be distinguished from faulty behavior and the discrepancies between the two must be noted. The fault root cause is identified and the control system is reconfigured in order to accommodate the fault, i. e. change set points, adjust control parameters or switch to different controller architectures. Applications of fault-adaptive control are mostly found in high-risk environments, such as aviation and life support systems. Examples include ISOGAI et al. 2000, KARSAI et al. 2001, NARASIMHAN 2002, SIMON et al. 2002, XIE et al. 2002, KARSAI et al. 2003, MANDERS 2003 and ABDELWAHED et al. 2005.

In the context of quality control in multistage manufacturing processes, fault-adaptive control is still far from being a reality. Further research is still needed on designing suitable feedback control architecture for such complex systems and on implementing efficient diagnostic models. The latter aspect, the diagnostic models, does not depend on the presence of a controller and thus should receive higher priority. In such situations, the term process *adjustment* [DEL CASTILLO 2002] is used rather than *control*, since these actions are often not automated. A third helpful research area is that of distributed sensing, which provides valuable in-process measurements as controller inputs [LIU & DING 2005, DING et al. 2006]. Nevertheless, the idea of feedback control based on quality inspection was handled in simpler processes. Most reported applications refer to SPC-based feedback control or run-by-run process control.

2.5.2.2 SPC-based feedback control

DEL CASTILLO 2002 draws the following comparison between traditional control or EPC and quality control. In engineering applications, controllers are usually implemented on commercially available components. In quality control applications, in contrast, the operator represents the controller and the feedback mechanism at the same time. Solely, neither SPC nor EPC can optimally control a manufacturing process [ELSAYED 2000, CHIU et al. 2003]. Practitioners of SPC argue that control actions are more likely to increase process variability because of the stochastic nature of manufacturing processes. However, by eliminating the option of control actions, SPC excludes opportunities for reducing the process output variability [SACHS et al. 1995].

Studies on integrating SPC and EPC report better performance than SPC or EPC alone [BOX & KRAMER 1992, DEL CASTILLO 2002, PAN 2002]. Generally, three aspects govern their integration, given that EPC is possible: measurement error, adjustment cost and sampling [SACHS et al. 1995]. HARDT & SIU 2002 consider three separate control loops as a guideline for EPC-SPC integration: equipment loop, material loop and process output loop (Figure 2.7). The process industry offers many examples of successful EPC-SPC applications [KUMAR 2005] because of the relative accessibility of process parameters in this industrial branch. PAN & DEL CASTILLO 2001 compare some process adjustment techniques and illustrate the advantage of their integration with EPC. Other examples are described in CHIU et al. 2003 and GUH 2003.

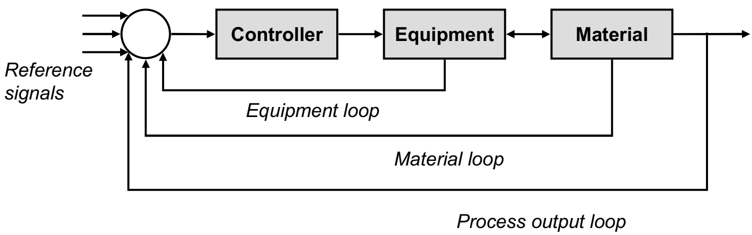

Figure 2.7: Three levels of feedback process control [HARDT & SIU 2002]

2.5.2.3 Run-by-run control

Run-by-run control monitors process parameters similar to SPC; however, unlike SPC, it makes continuous changes to the process in order to compensate drifts in the process outputs after every run based on objective functions such as the deviation from the target [KUMAR 2005]. The premise for run-by-run approaches is advanced in-situ inspection. Run-by-run control models describe the relationship between measurement and process variables. This type of control is sometimes termed model-based control [MUSACCHIO 1998]. Compared to conventional SPC, run-by-run control offers increased throughput, reduced operation errors and lower variability [MOYNE et al. 2000]. SACHS et al. 1995 propose a run-by-run controller with two action modes to deal with abrupt and gradual process changes, respectively. HARDT & SIU 2002 apply linear run-by-run controllers to a single stage bending process and to an injection molding process improving the process capability in both cases. RZEPNIEWSKI & HARDT 2003 explored the use of MIMO run-by-run controllers. They conclude that the MIMO control case is more sensitive to modeling errors, which are inherent in practical manufacturing applications. The industry has shown interest in the technique as well, especially in the process [KUMAR 2005] and in the semiconductor industries [MOYNE et al. 2000]. Figure 2.8 illustrates an example for a run-by-run controller developed for semiconductor manufacturing.

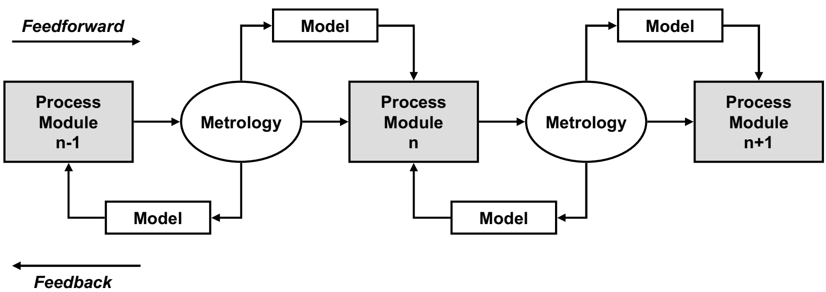

Figure 2.8: Advanced run-by-run process control [STRAATUM GROUP 2002]

2.5.2.4 Knowledge-based applications for process adjustment

Recent developments in AI and KBS research have resulted in the application of advanced diagnosis and process adjustment systems to manufacturing. Such systems are capable of instituting necessary adjustment and recovery procedures for minimal process interruption. SIMANI et al. 2003 refer to the integration of fault identification and process control as a promising future research direction. The knowledge-based process adjustment systems used for inline process control have a different decision strategy, but require the same input and output information and the same basic technical model of the process and the machine as any of the conventional process adjustment techniques [KUMAR 2005].

A model-based quality control loop for the chemical industry was introduced in PERNE & ENDESFELDER 1999. NORVILAS et al. 2000 presented an integrated fault detection scheme combining multivariate control charts of state variables and a diagnostic assistant for process monitoring and fault diagnosis in a polymerization reactor. According to the authors, classical fault diagnosis methods, such as residual based methods, were not effective for processes with autocorrelated univariate variables or correlated variables in multivariate problems.

The KBS approach was also implemented in quality planning and quality-related fault diagnosis. SCHÄFER 2003 presented a concept for process planning making use of a database of cause-effect relationships. The concept integrated quality planning, experience and statistical simulations with the process planning into one framework. The application of an ES for the enhancement of dimensional tolerancing and data analysis in quality control is reported in HOOKS et al. 1995. WESTKÄMPER 1994 applied machine learning algorithms towards zero-defect in process chains. A similar application is reported in MONOSTORI et al. 1996. Based on the state space approach, SCHOENENBERG 2000 presented a diagnostic system for multistage metal cutting operations. MARZOUKI et al. 1991 investigated coupling the electron-beam probing with KBS for fault localization purposes in VLSI-circuits[5] production. The authors described their work as a true progress in process automation compared to previous approaches, where the diagnosis task is left to the designer.

EICHHORN 2005 proposed the integration of 3D image processing for in-process quality control of large surfaces. The concept, which implemented neuro-fuzzy networks and statistical analyses, was applied to automotive BIW sheet metal parts. A system concept for integrated in-process acquisition and assessment of product characteristics and process parameters was presented in MÜLLER 2006. The validity of the concept was demonstrated on an automotive BIW station for adhesive application. OETZMANN 2005 discussed the construction of general purpose knowledge bases for production networks. His focus lay on measurement (quality inspection) and control (fault diagnosis and recovery).

In summary, KBS was proven successful and effective in dealing with real-life industrial challenges. It is also clear that the potential of KBS extends along the complete product life cycle from planning to inline inspection. This adds to the strength of the technique as it opens further possibilities for integrating product and process knowledge.

[5] Very large scale integrated circuits

2.5.3 Decision support issues

2.5.3.1 Uncertainty

A capacity of the human mind that challenges any algorithmic approach is the ability to classify items into classes whose meaning is well defined but whose boundaries are not well defined [ROLSTON 1988, YEN & LANGARI 1999]. To overcome this obstacle, a major concern in any application of intelligent systems is to include mechanisms for handling uncertainty.

Three categories of methods for handling uncertainty are often cited in the literature: formal probability, certainty factors and fuzzy logic [ROLSTON 1988, KASABOV 1998, GOEBEL 2006]. Reasoning based on formal probability, such as the interval of confidence [CARLSON & SÖDERBERG 2003] or Bayesian statistics [GELMAN et al. 2004], is a long established approach for quantifying uncertainties. When compared to frequentist statistics, Bayes' Theorem and, in particular, its emphasis on prior probabilities has caused considerable controversy. Proponents describe it as the best known way to deal with real-world uncertainties [GOLDSTEIN 2006]. I. J. Good, the leading statistician, argues that "*the subjectivist (i. e. Bayesian) states his judgments, whereas the objectivist sweeps them under the carpet by calling assumptions knowledge, and he basks in the glorious objectivity of science*" [GOOD 1976].

A simpler approach to dealing with uncertainty is that of certainty factors [ROLSTON 1988]. A certainty factor is a numerical value expressing the degree of belief in a conclusion. A value of 1 would mean total belief and a value of -1 would mean total disbelief. One early implementation of certainty factors in ES is reported in MYCIN [SHORTLIFFE 1976].

The third approach that gained wide acceptance is fuzzy reasoning. Fuzzy reasoning, first introduced by L. Zadeh in 1965 [ZADEH 1965], is a powerful tool to handle uncertainty due to incomplete or inexact information. The concept of a fuzzy set corresponds to meaningful classes with blurry boundaries [ROLSTON 1988]. The use of linguistic variables in fuzzy representation is a further advantage. Knowledge expressed in linguistic terms is easily comprehensible and transferable, thus resulting in significant savings in the design and maintenance costs of a fuzzy logic system. Many successful applications have established the technique in the field of diagnosis and control [ZIMMERMANN 1991, KOSKO 1992, ZHANG & MORRIS 1994, MENDEL 1995, DUBOIS et al. 1997, KASABOV 1998, YEN & LANGARI 1999, BALLÉ & FUESSEL 2000, MENZEL 2001, GUTMANN 2005]. The appendix includes a brief account of fuzzy math fundamentals.

2.5.3.2 Cost of quality (COQ)

The trade-off between product quality on one side and process adjustment costs on the other should be accounted for by the process settings, as it is unreasonable to aim at the best quality without bearing the cost factor in mind [HUANG 2001]. The problem is a simple fact of the market. All customers demand a product to be as close as possible to its nominal specifications, while manufacturers seek the largest possible tolerance to reduce the production costs [ROSS 1995]. Cost of quality (COQ) measurement was thus driven by the need in the industry for proper consideration of quality related costs in financial balance sheets.

The most common COQ model is the prevention-appraisal-failure model (PAF) introduced by FEIGENBAUM 1956 and MASSER 1957. The optimum cost of quality (PAF components only) is shown in Figure 2.9. The figure suggests that fault prevention is always more favorable, and that the cost optimum lies as near as possible to product perfection [PLUNKETT & DALE 1988]. Another famous cost model is the process cost model rooted in the work of Crosby [CROSBY 1979], which includes more intangible cost elements than PAF. Other approaches addressed integration with SPC [SON & HSU 1991], pictorial representation of COQ elements [CHEN & TANG 1992], and activity-based costing [TSAI 1998].

Representative reviews, discussions and application reports of quality cost models published in recent years are found in JURAN & GYRNA 1988, PLUNKETT & DALE 1988, BESTERFIELD 1990, ROSS 1995, GOULDEN & RAWLINS 1995, BURGESS 1996, KANER 1996, HWANG & ASPINWALL 1996, TSAI 1998, KUMAR et al. 1998, KRISHNAN et al. 2000 and SCHIFFAUEROVA & THOMSON 2006.

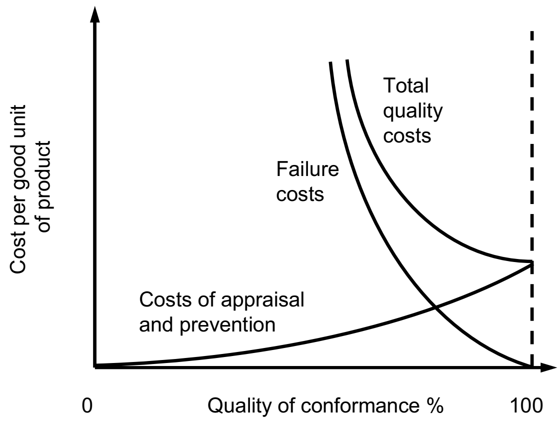

Figure 2.9: Optimum in quality costs [JURAN & GYRNA 1988, CAMPANELLA 1990]

The mentioned models handle tangible, e. g. material and scrap costs, as well as intangible aspects, e. g. loss of sales or loss of customer's goodwill. Including such intangible costs in COQ estimates is controversial. For example, KANER 1996 includes these costs and describes them as useful, while CAMPANELLA 1990 does not. JURAN & GYRNA 1988 recommend leaving these costs out of the quality balance sheet as the controversy over them may jeopardize the whole quality costing effort. In any case, these models do not quantify the actual product quality level in their calculations.

Taguchi's interpretation of COQ and his introduction of the quality loss function (QLF) [TAGUCHI et al. 1989] was a seminal effort linking product quality to quality costs. Taguchi's methodology relates any deviation from the target specification as a monetary loss and thus bases operational quality decisions on cost effectiveness [PEACE 1993]. His methods have been widely used for process optimization and improvement of overall process design and economics. Furthermore, his view paved the way for the incorporation of COQ aspects in online process control [TAGUCHI et al. 1989] and not only in planning and managerial contexts. Taguchi regards process improvement to include production parameter improvement, fault diagnosis and process adjustment methods with the aim that the total quality loss is minimized [TAGUCHI et al. 1989].

The implementation of QLF in its original form as suggested by Taguchi models deviations of quality characteristics in a quadratic form. Since its advent, several other variations to the QLF have been studied, such as asymmetrical loss functions [LI 2002, JOSEPH 2004], normalized loss functions [ANTONY 2001] and multivariate QLF [ANTONY 2001, CHOU et al. 2002, KO et al. 2005]. Practical applications of the QLF are found in NAYEBPOUR & WOODALL 1993, ARAVINDAN et al. 1995, HUANG 2001, CHEN et al. 2002, CHEN & CHOU 2004 and TSOU & CHEN 2005.

Although a large number of case studies of the offline implementation of COQ models and Taguchi's QLF exist, attempts to consider COQ or QLF in online process control are seldom [ARAVINDAN et al. 1995, NAYEBPOUR & WOODALL 1993, GUH & O'BRIEN 1999]. Generally, the use of economic models in inspection and quality control practices have attracted theorists only [CHEN & TANG 1992]. ARAVINDAN et al. 1995 stated that "*there is virtually no successful case study in the literature about the implementation of Taguchi's online quality control methods.*" The statement still holds to date.

Clearly, the integration of cost aspects in online quality control practices is still lagging in spite of its promise. Further development in this area would be equally helpful for run-by-run control applications, in the process industries for example, where the control strategy should take the economics of measurement and adjustment into account [SACHS et al. 1995]. The implementation of a simplified PAF model and quadratic QLF in quality-related decision-making are discussed in Chapter 7.

2.5.3.3 Human decision-making and error

The human role in modern manufacturing systems has been the subject of significant change. This is attributed to the increased introduction of automated machinery and complex IT structures. The role of human operators is currently associated with the idea of a supervisory controller [SHERIDAN 1987, DYM & LEVITT 1991].

In the context of fault diagnosis and recovery, the analysis of human decision-making [HATAMURA et al. 2003] and human error [DHILLON 2007] steadily gained importance in the industry. PAZ BARROSO & WILSON 2000 regard the human operators as potential *contributors* to a disturbance as well as *rescuers* of the process affected by the disturbance. When acting as rescuers, inappropriate decisions or actions on the part of the operators may exacerbate the fault severity and render an eventual recovery action more difficult. In their survey, PAZ BARROSO & WILSON 2000 show that 54% of the respondent companies find human error as a very important cause of disturbance. Studies show that approximately two thirds of the disturbances in industrial environments are related to human errors [CROSTACK & ELLOUZE 2003] that, apart from lacking process know-how, may arise due to emotional, cognitive, or social effects [NACHREINER et al. 2006, DHILLON 2007]. Such effects would manifest themselves more in highly automated processes, where an erroneous human action can have dire consequences. This notion led to the development of human-oriented automation paradigms [KRÜGER 2007] that reduce the possibility of human error and alleviate its consequences.

Nevertheless, the human expert remains the most intuitive resource for knowledge storage and reproduction, and represents the basis of all operational decisions and actions. Consequently, the need for objective decision support tools that amend the subjective human nature remains an interesting issue for both researchers and practitioners [LACKINGER & NEJDL 1993, DEXTER & BENOUARETS 1997, BAYDAR & SAITOU 2001, CROSTACK & ELLOUZE 2003].

2.6 Conclusion

It was shown that no sharp boundaries exist between the areas of process adjustment, quality control, and fault diagnosis and recovery. This is reflected in the literature where applications combine several aspects of these areas. Several researchers note the inconsistency in the used terminology and refrain from addressing this issue because of its little practical value.

SPC is by far the monitoring practice most widely used in the industry. However, with the current advances in inspection systems, it lost its position to 100% sampling schemes and distributed sensing. Furthermore, fault recognition in conventional SPC is outperformed by modern PR techniques. Among these techniques, NN stand out as a superbly robust and universally valid monitoring approach for real-world applications. The advantages of NN over traditional control chart monitoring methods include dealing with subsets of the monitored characteristics and capturing nonlinear multivariate relations. An increase in the number of NN applications for process monitoring could be observed in the last two decades. The early and effective recognition of unnatural patterns in the process behavior can narrow down the search space of the fault root cause and significantly accelerate the diagnosis procedure.

The core of the fault identification task is a model of the considered process. Model-based diagnosis provides the user with helpful information and directions for the fault recovery process. In many situations, however, the complexity of the technical system may not be described analytically with sufficient accuracy. In such situations where the available information is incomplete or imprecise, soft computing methods and knowledge-based diagnosis offer a robust way to overcome those problems. Surveys conducted in the past years show that KBS and rule-based reasoning have been very successful in fault diagnosis applications. In the automotive sector, relatively few KBS applications have been reported and the need for diagnosis systems that accommodate nonlinear process models still exists. Another advantage of model-based diagnosis systems is the good feasibility since no additional hardware is needed. Fault diagnosis algorithms can be implemented directly on process control computers.

The integration of fault diagnosis, quality control and process adjustment is a promising research direction that can contribute to higher productivity in manufacturing scenarios. Related research activities follow a closed-loop line of thinking when handling quality issues. The focus areas include the development of in-situ data acquisition schemes, the application of linear control algorithms and the incorporation of cost functions and optimization techniques. The use of such enhanced product models is useful for the overall process economics. KBS approaches are destined for success with complex production systems, where no single model can achieve satisfactory control actions. A combination of submodels supported by a KBS framework represents a powerful approach. To the best of the author’s knowledge, no previous research attempted building a KBS for online inspection and fault diagnosis in BIW assembly while employing soft computing and integrating design information, heuristics and quantitative decision criteria.

3 Field study

3.1 Overview

The chapter outlines a field study conducted in cooperation with the companies BMW AG and Perceptron GmbH.[6] The study attempted to stand on current practices in the BIW production process and to identify trends and future requirements related to quality control of BIW products. The assessment of losses incurred in terms of product quality deficits, types of faults encountered, and building a representative sample of faults for later verification are points that lie in the focus of the chapter.

The investigated BIW production facility is first described. The economical performance from a quality control perspective is then analyzed. A following section portrays the design, operation and inspection practices in BIW. A short account on the sources of variation in the stamping process is presented. The door assembly is closely examined as it will serve test and validation purposes at a later stage.

3.2 Description of the investigated production facility

3.2.1 General information

The automotive body production facility of the BMW AG factory 6.1 in Regensburg, Germany has a staff of approximately 2100 employees and produces approximately 1000 car bodies per day. The production is highly automated (>95% of the value added) and involves 971 welding robots. To finish a 332 kg BMW 1-series body, 5349 weld spots, 2.3 m weld seam and 41.5 m adhesive seam are needed. On average, a car body includes 550 parts which are principally assembled by robots with a small portion of manual activities. The employees, thus, focus more on quality assurance issues rather than on the production process.[7]

Vehicle assembly begins by adding single parts together into subassemblies. Basic subassemblies include the underbody, the motor compartment, the rear, the side frames, and the roof. These components are assembled into the main body structure. Doors, hoods, and deck lids are subassembled separately and added to the body at a later stage. Hence, BIW refers to the assembly process of stamped body parts into a complete vehicle body. The direct upstream process of BIW is stamping (press shop)

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[6] The field study was part of the research project ForWerkzeug-C2 funded by the Bavarian Research Foundation. The cooperating industrial partners were BMW Group <www.bmwgroup.com>, KUKA Roboter GmbH <www.kuka.com> and Perceptron GmbH <www.perceptron.com>.

[7] Source: <www.bmw-werk-regensburg.de>, accessed on February 1st, 2005

and the downstream process is the paint shop. Following the paint shop, the chassis, the motor, and the trim (windshields, seats, upholstery, electronics, etc.) are installed.

3.2.2 Facility performance from a quality control perspective

The facility produces seven different body models and implements inline product inspection in addition to offline measurement stations and a coordinate measurement machine (CMM) room. The investigated period included the SOP of two new models.

The overall equipment effectiveness (OEE) [NAKAJIMA 1988] is the main performance metric applied in the factory and is obtained by the multiplication of three ratios:

Availability ratio: time during which the equipment is actually available for operation divided by planned production time

Performance ratio: actual production rate divided by maximum capacity

Quality ratio: quantity of prime grade products divided by total production

On 28% of the working days in a period of thirty weeks, OEE violations were recorded. Table 3.1 gives a breakdown of the latter statistic for four door production lines. The unsatisfactory performance was mainly attributed to the availability ratio. The relatively long time needed for fault recovery was a major problem, while equipment performance and product quality were acceptable. This coincides with previous studies where waiting time was reported to take up to 90% of the total downtime [INGEMANSSON & OSCARSSON 2006]. It was found that costs pertaining to scrap, rework and adjustment, without consideration of the recovery time and effort, amounts to 1-2% of the production budget. Figure 3.1 gives an example of rework time of two vehicle models.

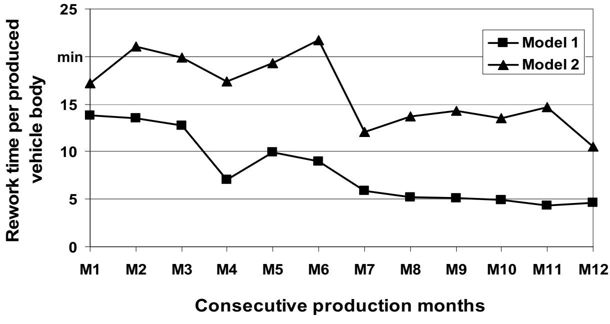

Figure 3.1: Rework time per produced vehicle for a period of twelve months

Table 3.1: OEE violation in four production lines

	Total production days considered	Planned OEE	Percentage of days where OEE was not maintained
Line 1	150	90%	4.7%
Line 2	147	90%	8.7%
Line 3	152	90%	6%
Line 4	150	90%	12%

Table 3.2 illustrates the significance of fault analysis costs and proper fault documentation. The table shows a sample, where analysis time was recorded for production faults of an underbody assembly line. Clearly, the time invested in fault analysis is much higher than that needed for the actual adjustment of the process. Such costs are usually regarded as overheads and are left out of any financial balance [TSAI 1998]. PLUNKETT & DALE 1988 note that the failure costs would increase drastically compared to appraisal and prevention costs if these overheads were included in the cost calculation.

Remark 1: Considering the observation results, it is clear that a change in the way quality related problems are handled is inevitable.

3.3 Vehicle body development process

3.3.1 Design and planning procedures

From requirements definition up to SOP, the product goes through a number of phases. BIW assembly is regarded as the least flexible in the overall vehicle assembly process [SEKINE et al. 1991]. The early planning phase combines available experience from previous models with new styling concepts. The process yields a project order and a preliminary proof of feasibility in the form of tolerance calculations.

Table 3.2: Sample showing fault analysis time versus equipment adjustment time (active maintenance time)

Fault case	Category	Analysis time	Adjustment time	Ratio of analysis time to adjustment time
1	Geometry	1 h	20 min	3
2	Equipment	2 h	10 min	12
3	Not documented	7 h	30 min	14
4	Geometry	1 h	15 min	4
5	Welding	20 h	2 h	10
6	Buffer	1 h	10 min	6
7	Geometry	7 h	30 min	14
8	Buffer	1 h	15 min	4
9	Geometry	2 h	1 h	2
10	Equipment	1 h 30 min	30 min	3

The concept phase identifies possible assembly schemes in agreement with established practices and experience. The gap target values provided from styling teams are then implemented to locate risk areas in the assembly operations and release a first dimensional concept of the vehicle, i. e. a first validation of the vehicle tolerance chain compatibility. The project then moves into the series development phase. This phase involves exhaustive simulations to assess and modify tolerance chains and risk areas. The goal is to develop a feasible tolerance scheme for preassembly tests.

The next phase is the pilot production, where the build process and tolerance chains are verified using hardware setups. Measurement schemes in line with the gap configuration and risk areas are then developed. Subassemblies are checked separately using cubings and later assembled into complete vehicles. Based on the observed deviations due to part and subassembly faults or due to process faults, the build process is revised. The result is an optimized build of the vehicle. Before transferal to operations, the product goes through the prevolume production phase, which includes process capability tests and final adjustments. The launch phase follows and is dominated by activities for variation source identification and reduction. During full production, maintenance and quality control tasks are prevalent.

As early as the concept phase, quality planning personnel are heavily involved in the development process. Thorough documentation of the results and intermediate approvals are maintained throughout the whole process. However, once the responsibility is transferred to the plant for series production, much of the process knowledge generated in the planning phases loses transparency. Final results, such as CMM measurement plans, are delivered to operation in more detail. But, a few of the operation staff gain an overview of the conducted fault root cause analyses, and the contributors to geometrical deviations.

Remark 2:	Much of the information needed for online fault analysis during operation is generated during the design and planning phases.

3.3.2 Stamping operations and BIW

Sheet metal parts assembled in BIW are the product of the upstream stamping process. Stamping variation is mostly expressed either as within-run or as run-to-run variation.[8] Other expressions for the variation include part-to-part variation, mean-bias deviation, and begin-end-of-run variation. The stamping operations in the production facility were not part of the field study. According to the experts in the production facility, limited success is reported in achieving low variation of stamped parts to design specifications. Recent research results supporting this opinion and describing solutions to overcoming the problem are found in ASP 2000a, CEGLAREK et al. 2001, HUANG & CEGLAREK 2002 and HOFFMANN et al. 2007.

Numerous factors affect the dimensional quality of the stamped parts. Steel grade and coating, part shape and size, die and press variables are among many factors that make the assignment of accurate design tolerances a tedious job. With such difficulties, some manufacturers operate presses outside statistical control. In a study by Auto/Steel Partnership[9] on stamping process variation [ASP 2000a], none of the participating manufacturers could successfully maintain a C_{pk} of 1.33 on all part dimensions using the original specifications.[10] This is particularly true for larger, less rigid body panels. Such parts are difficult to measure since fixtures often overconstrain the part and cause

8 Within-run refers to variations within the same batch of blanks, while run-to-run variation refers to the variation between different batches of blanks.

9 Further information on Auto/Steel Partnership is found at <www.a-sp.org>

10 A generally acknowledged standard value for minimum acceptable C_{pk} by automotive manufacturers

mean shifts. Also, rework may correct one particular deviation but adversely affect correlated points on the same part.

In recent years, an innovation of the Japanese industry known as *functional build* replaced the sequential BIW assembly paradigm [ASP 2000b]. Functional build focuses on the entire body rather than individual components. Components are evaluated relative to their mating parts and subsequent processes. Thus, it is tolerable to have larger mean shifts in stamped part dimensions, which are compensated for in the assembly.

In BIW, less rigid parts conform to more stable ones, making it difficult to predict the deviations in the final assembly. This explains the low correlation between stamping dimensions and assembly dimensions. In addition, assembly processes often distort parts during assembly, sometimes closer to and sometimes further away from nominal, because of clamping, spot welding, and inconsistencies of part locating schemes. Generally, assembly operations tend to reduce the mean bias while increasing the variation of panels.

Non-rigid parts build up rigid sub-assemblies, and tighter requirements for mean conformance, often normally distributed across an assembly, than those found in stamping are necessary [HU 1997]. The reason is the lower likelihood to compensate for out-of-specification dimensions of more rigid parts. For example, parallelism of feature lines of major closure panels after hemming operations is one such critical requirement. Moreover, manufacturers may improve the final dimensional quality of the assembly by adjusting the weld tools.

Apart from achieving acceptable dimensional quality, the process should minimize residual stresses in the resulting assemblies. The problem becomes relevant in the downstream paint shop. Here, thermal effects cause a relief of the residual stresses and local distortions of the assemblies. Therefore, most manufacturers install an additional geometry inspection stage after the paint process.

Remark 3:	BIW assembly offers higher potential for geometrical fault compensation, and is generally considered more critical than upstream processes.

3.3.3 BIW quality control procedures

Quality control of BIW assemblies comprises the inspection of the product geometry and controlling the surface quality. Both are EOL assessments, where no intermediate inspection is possible until the subassembly is complete. Product surface inspection is a human function conducted by trained line operators. The human eye detects nonconformances, such as scratches, weld splatter and dents, in a more economical and reliable manner than an automated system.

On the contrary, geometrical inspection is a highly automated task, where optical laser triangulation sensors are implemented. The inspection strategy and the accessibility of the monitored quality characteristics determine the sensor scheme. For 100% inspection, an inline measurement station would be a good alternative. Inline inspection systems are implemented for underbody, side apertures and the framing line, for example. For other subassemblies, such as doors and hoods, an offline station is installed for inspection on a sampling basis. Both types of measurement stations are equipped with stationary or robot-mounted sensors or a combination of both. The robot-mounted sensors, also known as flexible measurement systems (FMS), allow the inspection of different subassemblies. For example, the underbody in the case at hand is measured 100% inline using four robot-mounted sensors. An offline station with one robot is dedicated for sampling doors and hoods. Offline geometrical quality control methods additionally include CMM and hard gauge fixtures. The advantages of inline measurement systems can be summarizes as follows:

- Quick identification of process instabilities
- Quick reaction to faults and control of corrective action
- Lower risk
- Reduction of the rework costs
- Shorter measurement time with higher capacity
- Automatic measurement documentation

The one negative aspect of inline measurement is the relatively high initial investment. However, the cost development of such systems in recent years exhibited a downward trend that is expected to hold in the future. In the investigated facility, inline stations were installed for all large body groups of all produced models. A cost analysis in some cases even showed that the investment is justified merely by the savings during preproduction process capability tests.

Offline measurement stations offer the advantage of adapting to more than one part geometry at relatively lower initial investment. Compared to inline stations, the reaction time is longer because of the sampling strategy. Additional statistical analysis is needed in this case, which incorporates higher risk of undetected faults. Logistic costs increase since the vehicle or the subassembly has to be moved from the production line to the measurement station. The risk of station failure is higher because more production lines would be affected. Finally, liability to error increases due to the higher complexity of the measurement task.

A real-life example[11] illustrates the benefits of automated inline inspection. An inline station identified a missing punched hole. At the anticipated point of discovery the plant would have produced 625 bodies. To recover from the incident, the plant would have incurred 12.5 hours of downtime and 180 man-hours of rework at an estimated cost of 795,000 €.

Remark 4:	Automated measurement systems and 100% inline product inspection are becoming increasingly established quality control practices with proven economical and technological advantages.

3.3.4 Fault sources affecting dimensional quality of BIW

Excluding design errors, detected geometrical deviations in BIW assembly (Figure 3.2) arise from stamped parts, the assembly process (tooling and fixturing), human operation errors and measurement system errors. The effect of such sources on the final geometry is usually marked by both univariate and multivariate abnormalities in the monitored quality characteristics.

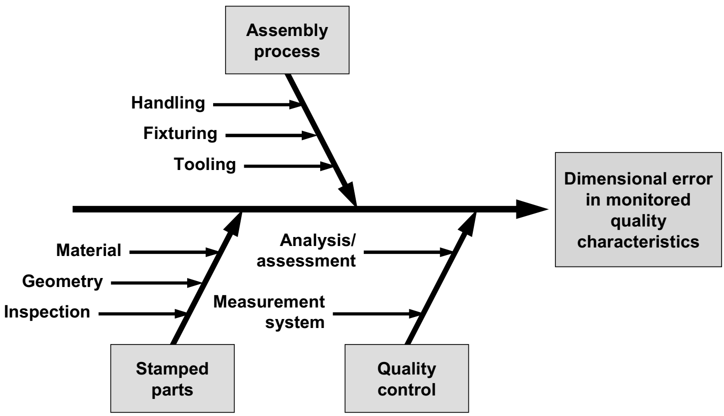

Figure 3.2: Sources of geometrical faults in BIW

[11] Courtesy of Perceptron GmbH

Stamped part variation is not a controllable parameter in the BIW assembly process. However, as mentioned previously, it can be compensated for using proper tool and fixture adjustment. The BIW assembly line is adjusted for new stamped part batches.

Observations in the factory show that tooling and fixturing are the main sources of detected faults. Over 50% of the documented fault cases could be attributed to these two factors. Tooling faults include, for example, robot path deviations, weld gun misalignment, welding tip wear or bolted joints errors. Also, the involved thermal effects, e. g. due to induction curing, represent sources of geometrical distortion.

Fixturing faults occur due to damaged clamps, worn locators or foreign inclusions preventing proper fixturing (e.g. weld splatter). The number of clamp adjustment instances undertaken in one year amounted to 7537, which corresponds to approximately 18% of the total number of clamps in the facility. Relevant experience from the literature suggests that fixture failures are a major reason for dimensional variation in automotive bodies [CARLSON & SÖDERBERG 2003]. A similar study by [CEGLAREK & SHI 1995] in the launch phase of an automotive assembly line estimated that 70% of the faults were due to fixturing problems. If interferences between handling and fixture locators occur, part handling may be a source of geometry deviations as well. As previously mentioned, the human error may not necessarily be confined to the manual manufacturing operations only. It extends to the quality assessment procedure as well. Some decisions regarding subassembly acceptance must be made based on experience. Factors like experience or mental and physical condition play a role in such a scenario.

Quality inspection forms another category of fault root causes. Temperature effects on sensor casing, lighting, and communication failure are examples of hardware failure of the sensor system leading to measurement faults. The measurement system may also deliver wrong values due to software failure, such as faulty algorithm parameters, short exposure time, deviating coordinate transformation and noise. Embedded diagnosis functionalities of the sensor system may be able to indicate some of these faults.

Excluding measurement faults, the observation of the BIW assembly faults suggests that fault root cause analysis is simpler using inline measurements. Mean shifts detected from the inline measurement stations could always be explained by corresponding changes in the process. Avoiding statistical uncertainties in the analysis renders the task more reliable. Furthermore, quick reaction to quality nonconformance is a must to maintain a stable process and minimize production costs. A seemingly intuitive and important notion is that trying to control the process without knowing the source of variation often leads to further instability.

Remark 5:	Inline measurement systems simplify fault diagnosis. However, they offer no fault analysis capabilities. Quick and reliable fault root cause analysis, an experience-exhaustive task, is the only guarantee to a stable process.

3.4 Door assembly

3.4.1 Assembly operations sequence

Although BIW does not formally include doors and hoods, the door assembly is a representative example of BIW assembly processes. Similar to all BIW assemblies, the door dimensional quality is determined along its history: stamped parts, assembly operations and sequence, hanging strategy and measurement procedures. In addition to possible build problems, the quality requirements of a door relate to basic comfort criteria, such as noise, water leakage, and poor fit.

The production line of a front left door of a passenger vehicle was closely examined. The line consists of two areas, a weld or header area and a finish area. The process involves sixteen assembly stations (AS) with eight robots and is operated by three workers. The daily production target is 700 doors. All fifteen parts of the door are shown in Figure 3.3. The figure also shows the assembly scheme of the studied door, starting in the upper left corner and ending in the lower right corner of the figure.

The weld area is where the geometry of the door is primarily defined. It is dominated by spot weld operations. The inner door panel (IP) serves as the principal locating panel for the assembly. Two geometry stations[12] exist in the weld area: AS 1 where the IP and the inner panel reinforcement (IPR) are assembled and AS 2 where IP+IPR and the outer panel reinforcement (OPR) are assembled. Other respot stations increase the rigidity of the subassembly. The finish area starts with the adhesive application on the outer panel (OP) and IP+OPR. Marriage between IP and OP takes place just before the hemmer. After the induction curing stage and mounting of the door auxiliary brake and hinges, the assembly process ends by visual inspection and storage.

Typical to the weld area, clamps and locators are used for fixturing, grippers for handling, and weld guns or torque-regulated screw drivers for joining. In all studied AS, overconstrained fixturing and not the theoretically sufficient 3-2-1 fixturing[13] is applied in order to reduce the variation of non-rigid parts. Stationary and robot-mounted welding guns join parts according to the AS layout. Door assembly strategies may differ from one manufacturer to another. The described sequence is one of several possible scenarios in the automotive industry.

[12] A geometry station is a station that contributes largely to the geometry in contrast to respot stations.

[13] 3-2-1 fixturing is a minimalistic fixturing scheme, where a part is fully constrained by fixing three points on the first locating plane, two points on the second and one point on the third, respectively. This is equivalent to constraining three translational and three rotational degrees-of-freedom of the part in question.

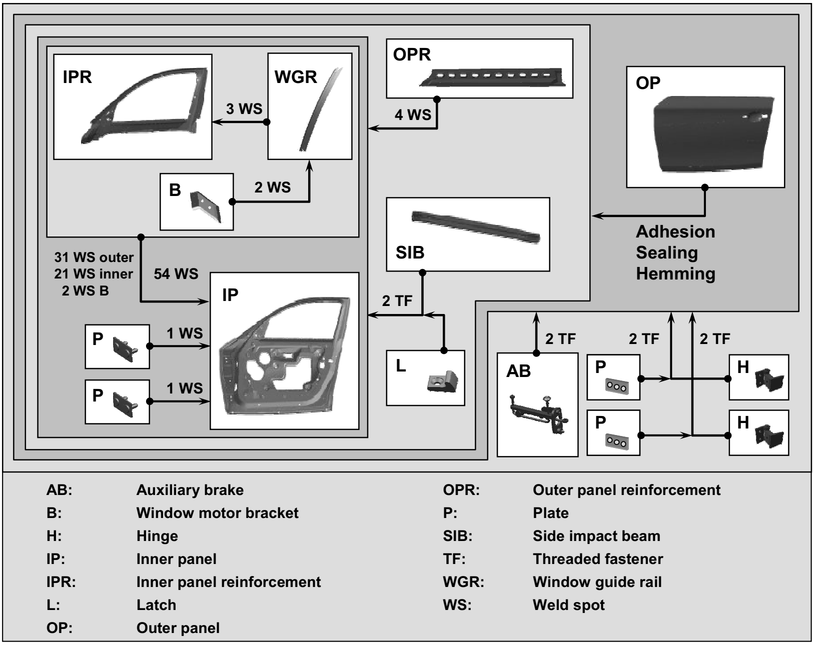

Figure 3.3: Parts and assembly sequence of the studied door

3.4.2 Door quality assessment

The key product characteristics of the door geometry are measured as gap and flush deviations. Considering the coordinate system in Figure 3.4, the in/out, or Y-axis, is the reference direction for flush-related measurements. The up/down, or Z-axis, and the fore/aft, or X-axis, refer to the gap between the door and the body.

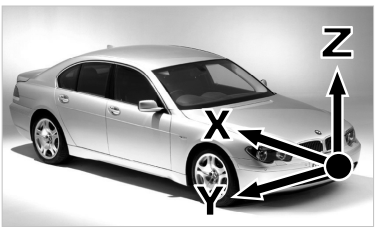

Figure 3.4: Body coordinate system

Figure 3.5 illustrates the door measurement scheme of the offline FMS. The gray highlighted measurement points (MP) are the six features used for visual fixturing of the door. Visual fixturing is a technique implemented by optical CMM that uses measured features to deduce the reference coordinate system. All other MP are referenced to this coordinate system.

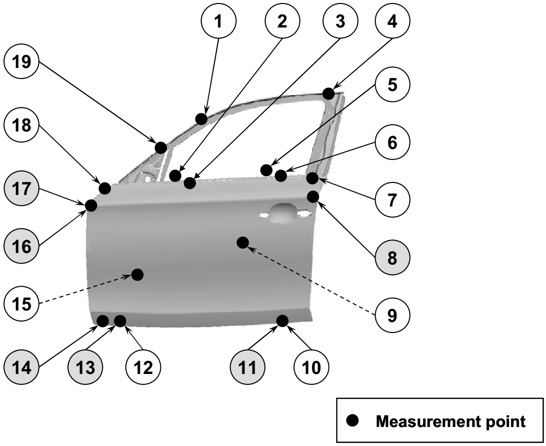

Figure 3.5: Door measurement scheme

Table 3.3 lists the MP, their design specifications and the implemented tolerance levels. The reference points are all chosen on the outer panel, as this relates directly to comfort criteria like noise and gap. If all MP fall within the specification limits, smooth door hanging is guaranteed later. The column *actual tolerance* refers to the values applied at the measurement station. The limits for reference MP are tighter. Other characteristics have more relaxed specification limits, where the build process and customer satisfaction are not critically affected.

Figure 3.6 shows the measurement results obtained from the door production line as deviations from nominal. Comparing the readings with the target process values in Table 3.3, the figure suggests that none of the MP conforms to the process requirements. Apparently, the observed mean shifts lead to the conclusion that the process has to be stopped and adjusted. This is, however, not true. In fact, the variation is more important than the absolute position of the process mean. As long as process adjustments can lead to a stable build, i. e. all MP exhibit an acceptable variation and the overall door geometry is valid for the downstream hanging strategy, the absolute mean value of single characteristics is of secondary interest. The main focus should be on reducing sudden drifts, shifts and variation within the same process run that distort the build.

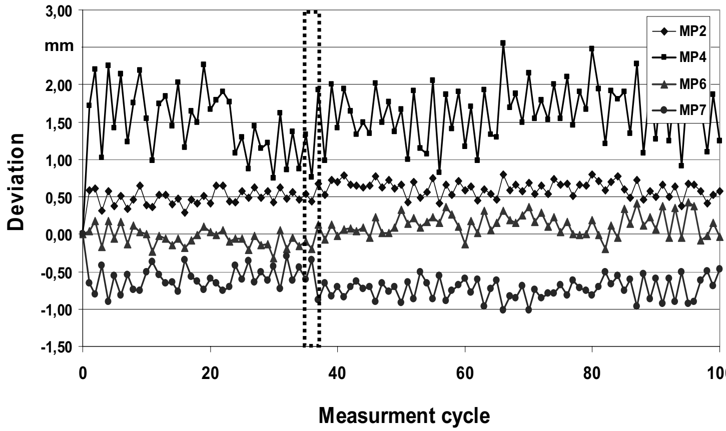

Figure 3.6: Measurement sample of four quality characteristics obtained from the studied door assembly line

Nevertheless, Figure 3.6 shows an incipient fault that occurred at cycle 36, where the mean values shifted slightly in a correlated manner indicating a special cause variation. Referring to Figure 3.5, the problem is in the gap between the outer and inner panels. The shift increased at a later stage and the process had to be adjusted. This and other fault cases are detailed in Chapter 6.

Lacking documentation transparency represented a considerable hindrance while collecting the material for this study. A log book is kept by the quality personnel that describes adjustment instances of the production line very briefly. The maintenance team keeps a similar log book for recording changes in equipment status. Measurement protocols from the inline measurement stations or the CMM are maintained by metrologists. To gain full overview of a fault case, one needs to consult all three sources and build the link between the detected abnormality in the measured data, the identified root cause and the countermeasure.

Remark 6:	Reliable monitoring of quality characteristics and solid process knowledge are key factors of efficient fault diagnosis and recovery.

Table 3.3: Measurement scheme of the door

MP	Design specification CMM (mm)	Actual specification OCMM (mm)	Actual tolerance OCMM (mm)	Axis	Quality characteristic	Feature
1	±2.0	±1.7	±1.28	Y	Flushness	Range
2	±0.5	±0.5	±0.38	Y	Flushness	Range
3	±0.5	±0.5	±0.38	Y	Flushness	Range
4	±2.4	±1.7	±1.28	Y	Flushness	Range
5	±0.5	±0.5	±0.38	Y	Flushness	Range
6	±0.5	±0.5	±0.38	Y	Flushness	Range
7	±0.5	±0.5	±0.38	Z	Gap (up/down)	Range
8	±0.2	±0.15	±0.11	Y	Flushness	Range
9a	±0.6	±0.6	±0.45	X	Gap (fore/aft)	Hole
9b	±0.6	±0.6	±0.45	Z	Gap (up/down)	Hole
10	±1.0	+1.6/-0.4	+1.35/-0.15	Y	Flushness	Range
11	±0.2	±0.15	±0.11	Z	Gap (up/down)	Edge
12	±0.5	±0.5	±0.38	Y	Flushness	Range
13	±0.2	±0.15	±0.11	Z	Gap (up/down)	Edge
14	±0.2	±0.15	±0.11	Y	Flushness	Range
15a	±0.6	±0.6	±0.45	X	Gap (fore/aft)	Hole
15b	±0.6	±0.6	±0.45	Z	Gap (up/down)	Hole
16	±0.2	±0.15	±0.11	X	Gap (fore/aft)	Edge
17	±0.2	±0.15	±0.11	Y	Flushness	Range
18	±0.5	±0.5	±0.38	Z	Gap (up/down)	Range
19	±0.5	+0.7/-0.3	+0.58/-0.18	Y	Flushness	Range

3.5 Conclusion

The field study shows that a change in the way quality related problems are handled is inevitable. It could also be illustrated that the information needed for online fault analysis during operation is mostly generated during the design and planning phases. Advanced 100% inline inspection offers a superb source of helpful process data but possesses no diagnosis capabilities. Solid fault root cause analysis is an experience-exhaustive task and the only guarantee to a stable process.

Comparing the findings of the field study to the conclusion of the literature review (Section 2.6), one observes how the industrial needs and the potential of available technologies can complement each other. Monitoring techniques can be extended to incorporate more advanced recognition algorithms. The human decision making process can be aided by tools for information and knowledge handling.

In addition to process-specific knowledge, the complex problem of fault diagnosis and recovery can be compactly described by a reduced number of factors. These factors address early recognition of unnatural process behavior, root cause identification and the justification of the recovery decision, and can be summarized as follows:

- Is the process stable?
- How can the process instability, if any, be described in terms of the behavior of single characteristics and their correlations?
- What is the possible root cause of the detected process instability?
- How accurate is the fault identification?
- How probable is the identified fault?
- When is it economical to adjust the process?

These six questions will shape the structure of the proposed solution and determine the methods described in the upcoming chapters. Further requirements that will be addressed implicitly include parameter accessibility, system modularity and compatibility with established standard procedures as well as economic efficiency.

4 Overview of the proposed system

4.1 Proposed system structure

This chapter serves as an overview of the proposed solution and the system components that will be detailed afterwards. It also sheds light on the rationale of the system structure based on the results of the literature review and the field study.

The proposed system, as seen in Figure 4.1, consists of six components in three modules that accommodate the tasks of fault recognition, fault identification and decision on the recovery action (refer to Figure 1.6). The six components must guarantee proper representation of the knowledge needed to answer the six questions listed in the conclusion of the previous chapter (Section 3.5).

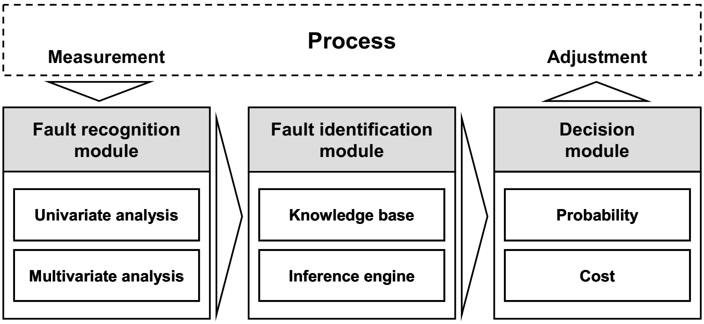

Figure 4.1: Components of the proposed system

The fault recognition module is responsible for process stability assessment. The goal is to enhance the early detection capability of existing monitoring systems w.r.t. univariate and multivariate abnormalities. It is proposed to use a neural network (NN) approach to build the module as discussed in Chapter 5.

The fault identification module (Chapter 6) consists of a knowledge base of the product faults and an inference engine that compares measured data with modeled fault cases and identifies the possible root cause. Thus, it is possible to shorten the fault diagnosis time, reduce costs and increase the reliability of the corrective action.

The decision module (Chapter 7) determines the statistical and economical validity of the recovery action at a certain moment. Given that the first two modules signaled and identified a fault, the two dedicated decision components determine whether a process adjustment should be conducted immediately or deferred to a later point. The a posteriori fault probability according to Bayes' Theorem is implemented as a measure for statistical validation. For process economy considerations, an approach based on the QLF is developed.

4.2 On the rationale of the proposed system structure

From a knowledge engineering viewpoint, the problem of fault analysis in BIW demands high experience and requires dealing with an abundance of data. Such a case can be best handled through hybrid knowledge representation techniques (Figure 4.2) [KASABOV 1998]. Hybrid methods promise a number of advantages in this regard such as combining heuristic and analytical knowledge, modularity, clear hierarchy and inherent stability. The proposed system structure can be seen to consist of a KBS core, a preprocessor for monitoring and a postprocessor for decision-making. It includes lower level elements for recognition, matching and classification as well as higher level elements for decision rules and strategic reasoning.

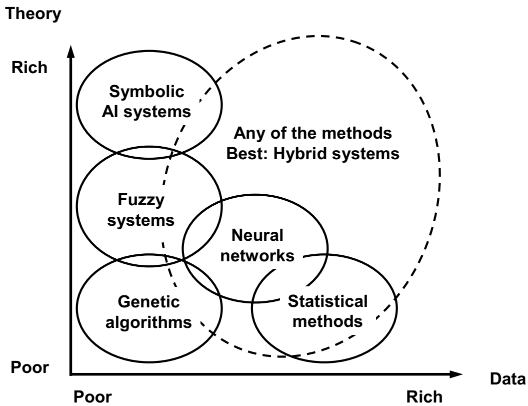

Figure 4.2: Usability of different methods of knowledge engineering and problem-solving depending on availability of data and expertise (theories) [KASABOV 1998]

For process monitoring, NN offer a number of advantages in statistical inference, such as the ability to model nonlinearities, minimal need of a priori knowledge or model assumptions, besides being adaptive, stable and robust in nature (refer to Section 2.3.4). Combined with 100% inspection, NN technology offers a competitive alternative to standard threshold-based alarm schemes. To overcome the disadvantages of NN as a black box approach, a multi-neural network (MNN) structure will be developed for univariate and multivariate assessment. Input data preprocessing will take place through normalization and scaling. No real-time execution problems are expected with the BIW production rate.

Knowledge-based systems (KBS) in multistage manufacturing are promising but yet sparingly applied in discrete manufacturing processes as compared to continuous processes, such as chemical plants. Mostly all effects in the automotive BIW are nonlinear, which renders the use of simple mathematical superposition for determining the process behavior invalid. In addition to the difficulty in modeling BIW assembly processes, continuous online parameter adjustments increase the effort, and thus the running costs, of maintaining a complex analytical diagnostic model drastically. KBS frameworks are favorable in safestoring analytical and expert knowledge efficiently. The 80%-20% rule [KINGSTON 2004] renders the design of KBS in comparison to an exact mathematical model extremely economical. The latter rule is a common practice in the KBS design. It refers to including 80% of the required knowledge in the KBS and leaving 20% to the human expert. This is often not possible for analytical models.

The knowledge base will be designed in the form of production rules combining process heuristics with simulation results of numerical and analytical models. The rule-based approach has a number of weaknesses such as lack of generality and poor handling of novel situations but it also offers efficiency and effectiveness [ANGELI & CHATZINIKOLAOU 2004]. The drawbacks will be addressed through the fuzzy inference engine and the conflict resolution strategy that attempt to exploit stored knowledge on different diagnosis levels.

As the considered BIW process does not possess a feedback control architecture, the feedback aspect of the proposed solution is basically a decision support task, i. e. the operator is provided with suggestions for further actions. The main factors here are the fault probability and the process economy that the operator subconsciously considers based on his experience. For an online implementation, these factors have to be identified. The foremost approach to the problem of a posteriori probability is the Bayesian statistics. For the process economics part, QLF is the base of all known approaches to quantifying product quality on a monetary basis. Both approaches are applied for both tasks, respectively. The fault probability component is thus a final uncertainty absorber in the system structure, besides the NN in the recognition task and the fuzzy inference engine in the identification task.

4.3 Assumptions

The running process is assumed to be capable and stable. Fault detection takes place before the process departs the tolerance limits, i. e. incipient fault. 100% sampling is assumed. Only variable characteristics will be measured, specifically automatically measurable nonconforming geometrical quality characteristics. Statistically independent nominal-the-best[14] features are considered for monitoring. The fault knowledge base consists of predefined fault cases and can be extended in offline mode and then reimplemented. The presence of multiple simultaneous fault root causes will not be considered, since such a case often results in uncorrelated data behavior, and the dimension of the identification problem would increase drastically. The assumptions are necessary in order to limit the problem complexity. Otherwise, the system requirements would be too generic to fulfill, ultimately reducing the effectiveness of the solution.

The system structure proposed in this chapter will be detailed in the three following chapters describing the fault recognition module, the fault identification module, and the decision module, respectively.

[14] Nominal-the-best quality characteristics refer to features that are assigned upper and lower tolerance limits, such as most geometrical quality characteristics of BIW. In contrast, larger-the-better features are assigned lower tolerance limits only (e. g. purity of chemical substances). Similarly, smaller-the-better features are assigned upper tolerance limits only (e. g. surface roughness of polished surfaces).

5 Fault recognition module

5.1 Overview

The goal of this chapter is to develop a generic structure for monitoring multiple product quality characteristics. The module focuses on the early recognition of fault patterns in the product. The term *early* refers to the detection of faults while the process is still within the allowed tolerance field. A NN approach is followed for the fault recognition task. The monitoring strategy and the statistical data distribution model are addressed before presenting the module structure. The NN are iteratively optimized and test results are described. Finally, a summary and remarks on the practical implementation of the module are given. Figure 5.1 shows the two major components of the module.

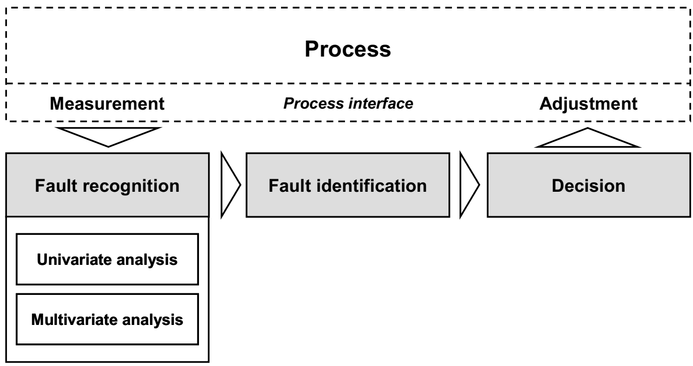

Figure 5.1: Components of the fault recognition module

5.2 Process considerations for network design and training

5.2.1 Monitoring strategy

The monitoring strategy applied in the studied production facility is similar to precontrol (refer to Section 2.3.2). The tolerance or alarm limit is set to 75% of the specification limit for all MP. This is generally true for the door assembly as well as for other BIW assemblies. The most common unnatural patterns according to the field study were mainly sudden shifts or trends in the process mean that may be accompanied by increased variation. Other patterns, such as systematic or cyclic variation, were only occasionally observed. Therefore, the module considers monitoring shifts and trends of the quality characteristics only. Both small and large process mean deviations as well as correlation analysis have to be addressed.

In order to generalize the use of the module, absolute measurement values are avoided in the training process. The NN training data depends on the standard deviation (σ) of the process as a measure of process stability. The amount of deviation from the desired target value is expressed in units of σ. Three categories of deviation are defined as follows: small (≤1σ), moderate (>1σ and ≤2σ) and large (>2σ). Consequently, a large shift is one where the process mean moves suddenly beyond the 2σ limit. Similarly, a large trend is a trend that moves the process more than 2σ away from the desired target value within a defined window. According to this definition, a process with $C_{pk} \geq 1.33$ that exhibits a small mean shift still lies within the tolerance boundaries. Consequently, if the recognition module is sensitive to deviations less than 1σ, fault detection takes place before the product is rejected, which is the case with the door assembly process.

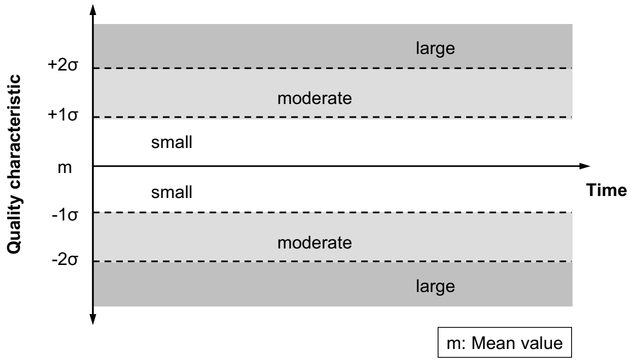

Figure 5.2: Deviation classes w.r.t. standard deviation

5.2.2 Statistical distribution model of monitored characteristics

To generate the NN training data, it is necessary to gain knowledge of the statistical distribution model of the monitored characteristics. For this purpose, process data was tested[15] for their actual distribution models and for normality. Three different sample sizes were chosen to represent long and short process sequences. Long sequences had

[15] Tests were conducted using the software packages QS-Stat and Matlab.

a sample size of 1000. For short sequences, sample sizes of 100 and 50 were tested. The longer sequence gives a more true distribution of the considered characteristic. The smallest sample size was chosen to represent the typical window size for short-term process monitoring. The behavior of such small sample sizes is interesting for network training since a smaller window size leads to quicker fault recognition. The fact remains, however, that smaller sample sizes are associated with greater uncertainty of the distribution model.

In the conducted tests, the same distribution model for each quality characteristic was obtained regardless of the sample size. The distributions varied between Weibull, mixed and normal distributions. Two normality tests were applied next. The Shapiro-Wilk test calculates a statistic that tests whether a random sample comes from a normal distribution. The higher the value of the test statistic, the closer the expected distribution is to normality. The test performs very well in comparison studies with other goodness-of-fit tests[16]. It is particularly efficient in checking the tail regions of the distributions, which are of special interest in quality applications [DIETRICH & SCHULZE 1999, FUKUNAGA 1990, MONTGOMERY 2001].

The second test is the Lilliefors test or the Lilliefors modification of the Kolmogorov-Smirnov test. The Kolmogorov-Smirnov test and its Lilliefors modification are sensitive to deviations in the midrange, which are not usually the kinds of deviations that lead to inference problems. The Lilliefors test evaluates the hypothesis that a data sequence has a normal distribution with unspecified mean and variance, against the alternative that it does not have a normal distribution [FUKUNAGA 1990, MONTGOMERY 2001].

A confidence level of 5% was implemented for both tests. Random sequences were obtained from the investigated production line at periods where the process mean was stable. The fifteen quality characteristics (Figure 3.5) met the normality requirements of both tests for 100% of the tested sequences at sample sizes n=100 and n=50. For a sample size of n=1000, a minor fraction of the sequences failed the normality tests. Table 5.1 gives an overview of the results.

Similar studies show that the assumption of normality is a valid approximation in geometrical tolerance chains. MANNEWITZ 2004 stated that for a four-element linear tolerance chain and more than fifty samples, a normal distribution can be assumed with sufficient accuracy. Most tolerance chains in the automotive body fulfill these conditions. In a study on quality cost estimation, GUH 2002a and GUH 2002b report that if the process is performing well, data non-normality affects the recognition very slightly. WHEELER 1995 and HOERL & PALM 1992 take the same position and regard the assumption of independence and normality as a welcome generalization in industrial practices. ZORRIASSATINE et al. 2005 argue that, even with expert knowledge of a

[16] Goodness-of-fit tests are statistical tests of the validity of a certain hypothesis without the specification of an alternative hypothesis.

system, it can be difficult to predict how distribution properties and correlations will change when abnormal states start to occur. Based on the presented test results and relevant literature, the independence and normal distribution of the training and test data will be assumed.

Table 5.1: Percentage success of normality tests

Sample size	Shapiro-Wilk	Lilliefors	Both tests
50	100%	100%	100%
100	100%	100%	100%
1000	95%	99%	95%

5.2.3 Error type I and error type II

A well designed monitoring technique is one that reconciles effectively between error type I and error type II. Error type I refers to identifying in-specification products as defects, i. e. false rejection, while error type II refers to defects being identified as in-specification, i. e. false acceptance. The errors type I and type II are also known as the false alarm rate and the escape rate, respectively. The training process will attempt to reduce these errors to a minimum.

Another quantitative measure of this problem is the average run length (ARL). The ARL is a widely accepted measure used to evaluate and compare monitoring methods. Any sequence of samples that leads to an out-of-control signal is called a *run*. The ARL is defined as the expected number of samples taken until an out-of-control signal is issued [DIETRICH & SCHULZE 1999, KUME 1985]. The NN will be trained to generate signals as quickly as possible if the production process is out-of-control (ideally ARL=1) and as late as possible (ideally ARL=∞), if the production process is in-control.

5.2.4 Evaluation criterion

To evaluate the classification capability of the module components, a classification rate is defined as

$$\text{Classification rate} = \frac{\text{Number of correctly recognized patterns} \cdot 100}{\text{Total number of patterns}} \% \qquad (5.1)$$

The classification rate depends on the choice of a suitable numerical truth value or a threshold. When the output of the NN corresponding to a certain unnatural pattern exceeds the assigned truth value, the pattern is assumed to exist and an alarm signal is triggered. Thus, the truth value represents a balance between error type I and error type II.

5.3 Module structure

The proposed module structure shown in Figure 5.3 resulted from preliminary trials to fulfill the process requirements discussed in Section 5.2. The module is designed to recognize unnatural patterns in univariate data as well as correlations in bivariate manner in two separate stages. Each of the shaded blocks in Figure 5.3 represents a single NN with a reference index. For example, NN-123 refers to network 3 in step 2 of stage 1. Measurement data from all monitored quality characteristics is fed sequentially to the module using a multiplexer function. The measured quality characteristics represent the input to the module. The output of the module includes an assessment of the stability of each measured quality characteristic (univariate) as well as the identification of correlations between the measured characteristics (multivariate).

The first stage of the system is a two-step classifier that assigns the input measurement data of any arbitrary quality characteristic into one of five categories. The five categories are normal behavior, upward shift, downward shift, upward trend and downward trend. This is repeated for all monitored characteristics using the same network system. The first step of the stage is a general-purpose network trained to recognize all five deviation patterns. It acts as the main fault pattern classifier. A second classification step consists of five special-purpose networks corresponding to the considered deviation patterns. The networks of the second step have a two-fold purpose. Firstly, they retest the measurement data for the existence of the unnatural pattern, thus improving the classification accuracy. Secondly, the output values of NN-121 to NN-125 are indicators of the deviation magnitudes.

The second stage is a correlation observer that implements a novel monitoring concept. The results of stage one, and not the original measured data, are compared in bivariate manner to detect pattern similarities. The two NN of the second stage categorize the correlation patterns between the measured product characteristics into five different correlation classes to construct a correlation matrix: weak positive, strong positive, weak negative, strong negative and no correlation. In this way, unnatural behavior in subsets of the monitored characteristics can be readily detected. This is advantageous in contrast to many multivariate control charts, where the evaluation is based on an overall statistic [NIAKI & ABBASI 2005]. This concept also offers beneficial perspectives in dealing with nonlinearly correlated data sequences.

The proposed structure is a MNN with serial and parallel processing. The use of MNN architectures, in contrast to a single network, is the better approach for achieving more intelligent behavior [MADANI 1999]. MNN are characterized by enhanced overall training efficiency and superior generalization. For example, if only one network is used for the univariate analysis stage instead of six, the network size would be very large and training can easily fail due to interferences between the considered patterns. Also, by portioning a complex mapping task, such modular architectures tend to find representations that are easily interpretable.

The factors affecting the design of NN systems listed in Table 2.2 are discussed next.

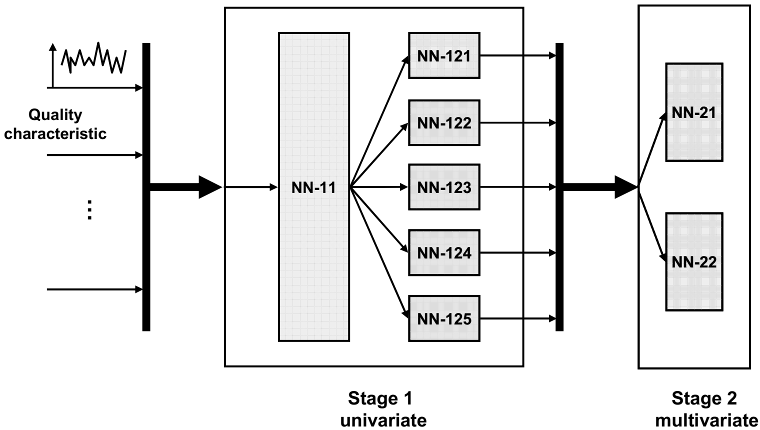

Figure 5.3: Structure of the fault recognition module

5.4 Development of the neural network paradigm

5.4.1 Network structure

Since the networks of both stages have similar tasks, they all share the same basic configuration, i. e. the same network architecture, neuron type, and learning algorithm. The general attributes of the applied network paradigm are briefly described next. An account of neural network fundamentals is also found in the Appendix.

Multilayer feedforward neural network (MFNN)

The network is a multilayer perceptron network (Figure 5.4) and has only feedforward information transmission from the lower neural layers to the higher layers. A feedforward NN can be regarded as a nonlinear mathematical function which transforms a set of input variables into a set of output variables [BISHOP 1994].

Fully connected neural network

All possible forward connections are existent and possess weights.

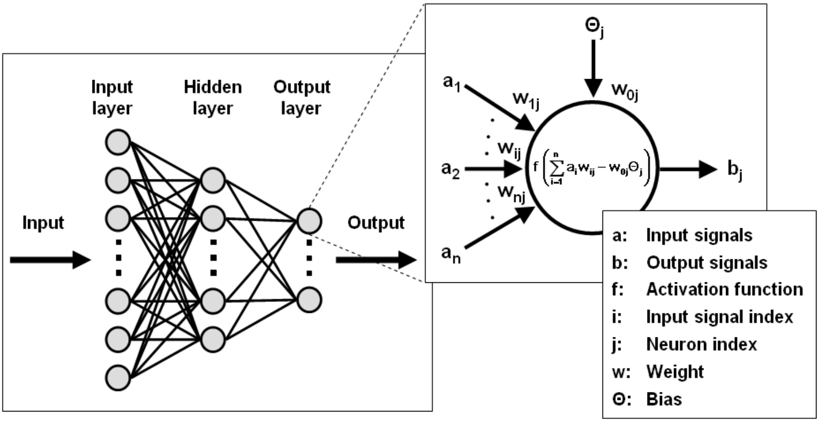

Figure 5.4: Topology of a three-layer MFNN

Static network

The network is a static neural model in the sense that its input-output relationship may be described by a memoryless algebraic nonlinear mapping function. Hence, once the network is trained, its outputs are dependant only on the current inputs.

Three-layer network

GUO & DOOLEY 1992 point out that there is no standard way of determining the number of hidden layers. In a survey of NN applications [ZORRIASSATINE & TANNOCK 1998], most NN designs depended on trial-and-error to determine the number of hidden layers. In many cases three layers were sufficient to model the problem addressed. More recently approaches to the fusion of NN with optimization algorithms and other technologies, such as genetic algorithms [KASABOV 1998] were discussed. Several sources [CYBENKO 1989, HORNIK et al. 1989] recommend that one hidden layer is sufficient to model any complex system with sufficient accuracy. The networks implemented in this module consist of three layers; an input, a hidden and an output layer.

Number of neurons per layer

The number of neurons in the input and hidden layers will be determined based on simulations. The tests involve real data from the automotive door production line and generated data. Determining the number of output neurons of a network is straight forward since the number of output classes is known.

5.4.2 Learning

Supervised learning

In supervised learning, the networks are trained on a prearranged data set, called training data set in which each pattern is labeled with its true class label, i. e. input-output data pairs are fed to the network during training [HAYKIN 1999].

Batch training with random pattern introduction

Batch training refers to updating the network connection weights and biases only after all the inputs and targets are presented, i. e. all weight changes are introduced as a sum once for every data batch. This type of training is suitable for static NN. It is in most cases slower than sequential learning (pattern-by-pattern) but offers a more accurate estimate of the error gradient. It also allows for more choices of the training function [HAYKIN 1999]. This type of training will be implemented for the developed NN.

The learning process is maintained on an epoch-by-epoch[17] basis until the weights are stable and the training error converges to a minimum. The training patterns will be randomized from epoch to epoch before being introduced to the networks. The randomization tends to make the search stochastic over the learning cycles and limits the possibility of local minima. The strategy also helps in avoiding the phenomenon of catastrophic forgetting.[18]

Backpropagation

The backpropagation (BP) algorithm is the most effective weight updating method of MFNN [GUPTA et al. 2003]. Among supervised learning algorithms, BP is probably the most widely used for error function evaluation. The original BP algorithm [RUMELHART et al. 1986] and its extensions accommodate parallel computational structures, can store more patterns than the network inputs and are able to perform complex nonlinear mapping. A BP network usually outperforms other network types

[17] An epoch is one complete presentation of the entire training set during the learning process.

[18] Catastrophic forgetting refers to the ability of the NN to forget what it has learned from previous examples, when they are no longer presented to it.

such as learning vector quantization networks and radial basis function networks in classification problems.

BP generally converges slowly compared to other algorithms. It is, however, simple to implement and the recall speed is not affected by the training performance [SAGIROGLU et al. 2000]. Successful applications of BP networks for process monitoring are also reported in the literature [PUGH 1991, HWARNG & HUBELE 1993]. The BP algorithm will be applied to train all system networks. The appendix gives a mathematical description of the algorithm.

Faster derivations of the standard BP algorithm fall into two main categories. The first depends on heuristics such as applying adaptive learning and including momentum constants. The second category depends on the use of standard numerical optimization techniques such as the Quasi-Newton methods. Comparison results given in [THE MATHWORKS 2007] suggest that for a PR problem of similar order as the one at hand, BP with heuristic techniques is the most suited. The applied BP training algorithm will include adaptive learning rate adjustment and the use of a momentum constant.

5.4.3 Activation function

Activation functions map a neuron's input domain to a prespecified output range. Typical activation functions are shown in Figure 5.5. The sigmoid function, whose graph is s-shaped, is by far the most common form of activation functions used in NN design. It is defined as "*a strictly increasing function that exhibits a graceful balance between linear and nonlinear behavior*" [HAYKIN 1999].

The hyperbolic tangent function, which is a smooth sigmoidal nonlinear function, will be implemented for the input and hidden layer neurons. It is s-shaped and allows for negative values of the activation function. Antisymmetric activation functions tend to learn faster than otherwise [HAYKIN 1999]. They are differentiable and, hence, suited for the BP learning algorithm. The hyperbolic tangent function is a good tradeoff for NN applications, where the processing speed is more important than the exact shape of the activation function. For the output layer neurons the logistic sigmoid function with output range [0, 1] and the linear function will be compared. Other features of the networks will be determined using trial-and-error to achieve better NN performance.

5.4.4 Training data

The quality of training and test data is crucial for the performance of the NN. A training vector in supervised learning consists of two parts: an input pattern and a corresponding output target. The target input part is addressed here, while the target output part is discussed in the following sections. The training data is processed in standard

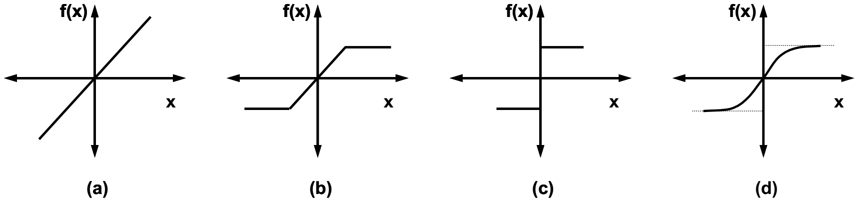

Figure 5.5: Typical activation functions (a) linear, (b) ramp, (c) threshold (d) hyperbolic tangent sigmoid

form following a normal distribution N~(0,1). Two types of data were used to construct the input patterns: simulated and real data. In both cases, the output patterns are the target network outputs as defined by the desired output classes.

Simulated input data

Simulated data was generated such that each abnormal pattern consists of an in-control mean, a common cause random noise and a deviation representing an assignable cause. Input data patterns were generated using the following equation:

$$x(t) = m(t) + v(t) + q(t) \tag{5.2}$$

where t is time of sampling, x(t) the normalized value of the quality characteristic at time t, m(t) the process mean, and v(t) the common cause variation following a distribution N~(0, σ), where σ is the process standard deviation. The value of σ is normalized to 1, so that v(t) is generated as N~(0, 1). q(t) is the assignable cause disturbance at time t. For normal behavior:

$$q(t) = 0 \tag{5.3}$$

For shifts in the process mean:

$$q(t) = u \cdot d \tag{5.4}$$

where u determines the point at which the shift starts (u = 0 before shifting, u=1 after shifting) and d the magnitude of the shift in terms of σ.

For trends:

$$q(t) = s \cdot t \tag{5.5}$$

where s is the trend slope in terms of σ. Table 5.2 gives the intervals of the parameters d and s in order to generate small, moderate and large deviations as shown in Figure 5.2. The table assumes σ=1 and a measurement sequence of thirty-five products (input vector size) to calculate the slope value s. Step sizes of 0.6 and 0.02 were implemented for mean shifts and trends, respectively.

Table 5.2: Parameter intervals for input pattern generation

Deviation	Shifts	Trends
Small	$d \leq 1$	$s \leq 0.03$
Moderate	$1 < d \leq 2$	$0.03 < s \leq 0.06$
Large	$2 < d$	$0.06 < s$

Real input data

Process data from the production line described in Chapter 3 was normalized and scaled before being introduced to the NN system. The data sequences chosen included normal process behavior as well as fault cases, where shifts and trends were observed. The procedure is described by the following equation:

$$z(t) = \frac{y(t) - E(\mu)}{E(\sigma)} \tag{5.6}$$

where z(t) is the standardized form of the process data, y(t) is the real process data, E(μ) is the expected mean and E(σ) is the expected standard deviation.

This procedure is also intended for the online application of the system. A normalization and scaling scheme prior to the actual data analysis by the NN system allows for a more flexible adjustment of the specification limits, and stresses the generic character of the designed NN system. In practical application, m and σ are estimated directly from available data samples.

5.5 Stage 1: Univariate stage

5.5.1 Step 1: General classifier (NN-11)

5.5.1.1 Training and test procedures

An important issue in monitoring applications is the number of neurons in the input layer. It corresponds to the length of the process sequence observed, referred to as the recognition window size. The size of the recognition window can greatly influence the recognition performance of the system. A small window size might result in insufficient recognition (increased error type I) because the amount of the available process data is not enough to represent all recognition features of the patterns. Meanwhile, a large window size could result in longer pattern detection time. In related literature, several window sizes ranging from five to sixty are described [GUH & TANNOCK 1999a].

Also, the number of neurons in the hidden layer has a significant effect on the performance of the network [TANG & FISHWICK 1993]. Rules of thumb and systematic tests are proposed for determining the number of hidden neurons [HECHT-NIELSEN 1990]. For example, GUPTA et al. 2003 suggest using the number of input data classes for this purpose. Using fewer neurons than needed reduces the recognition capability of the network. On the other hand, if the hidden layer contains more neurons than necessary, the generalization capability of the NN may be damaged.

The output of NN-11 determines which of the five patterns exists in the process sequence. The five patterns are normal behavior, upward shift, downward shift, upward trend and downward trend. Hence, the output layer has five neurons, where each neuron corresponds to a pattern and outputs a value between 0 and 1. An output closer to 1 indicates a higher matching degree with a specific pattern. An output closer to 0 means that a pattern was probably not detected. The target value was reduced from 1 to 0.9 in order to prevent output neuron saturation. Table 5.3 gives the target output of the five output neurons for the five pattern categories.

Table 5.4 gives an overview of the implemented training parameters of NN-11. While testing the performance of the network w.r.t. a certain parameter, the other parameters assumed their assigned default values given in brackets. The default values were arbitrarily chosen in the mid-interval of the solution space.

The training patterns were equally divided among normal process behavior, mean shift and trend, respectively. For each of the three cases, 2000 vectors were used for training and 2000 for testing. According to the data generation scheme described in the previous section, the training vectors consisted of 80% simulated data and 20% real data. The test vectors had an equal number of simulated and real training patterns. The real data portion helps to train the network to deal with noisy input signals. The initial network weights and biases were set using asymmetric random initialization.

The number of training patterns fulfills the Vapnic-Chervonenkis (VC) dimension rule [KASABOV 1998]. The VC dimension is a quantitative measure of how many randomly chosen training examples are necessary for correct function approximation. For a three layer feedforward network with n_1, n_2 and n_3 neurons, respectively, the VC dimension is given by the following equation.

$$\mathrm{VC\,dim} \geq n_1 n_2 + \frac{n_2}{2}(n_3 - 1) + 1 \tag{5.7}$$

Table 5.3: Output format of NN-11

Normal	Upward shift	Downward shift	Upward trend	Downward trend
[0.9, 0, 0, 0, 0]	[0, 0.9, 0, 0, 0]	[0, 0, 0.9, 0, 0]	[0, 0, 0, 0.9, 0]	[0, 0, 0, 0, 0.9]

Table 5.4: NN-11 training parameters

Network parameter	Range (default value)
Range of input signals	[-5, 5]
Number of input neurons	20 to 60 (35)
Number of hidden neurons	15 to 45 (30)
Number of output neurons	5
Input / hidden neurons activation function	Hyperbolic tangent sigmoid
Output neurons activation function	Logistic sigmoid or linear (linear)
Learning algorithm	Gradient descent with momentum and adaptive learning rate backpropagation
Initial learning rate	0.01
Momentum constant	0.9
Learning rate increase factor	1.05
Learning rate decrease factor	0.7
Maximum performance increase	1.04
Performance function	MSE (mean square error)
Maximum epoch number	2000
Training goal	0.02
Truth value (recognition threshold)	0.2 to 0.7 (0.4)

5.5.1.2 Simulation results

Two criteria were implemented to evaluate and optimize the network structure: the residual mean square error (MSE) after the training procedure and the classification rate defined in Section 5.2.4. Differences in the recognition results due to the random initialization were negligible and did not exceed 1% in all design parameters. The diagrams in this section include the best values reached in the course of the simulation.

Number of input neurons

The number of input neurons represents a compromise between detection time and certainty, which are naturally inversely proportional. Based on the results shown in Figure 5.6 and Figure 5.7, it is suggested to implement an input window size of forty samples. This value should fairly accommodate both time and certainty requirements and balance the risk between faulty and delayed data interpretation.

Number of hidden neurons

With an increasing number of hidden neurons, the final training error exhibited a similar behavior as that in Figure 5.6 and nearly settled at twenty-five hidden neurons. The classification rate was best at twenty and twenty-five neurons. In Figure 5.8, the curve indicating the classification rate is typically flat. A lower number of hidden neurons does not capture the patterns well enough, while the deterioration at a higher number of hidden neurons is explained by overfitting. The phenomenon was especially critical at values higher than forty-five neurons. A number of twenty-five hidden neurons will thus be implemented.

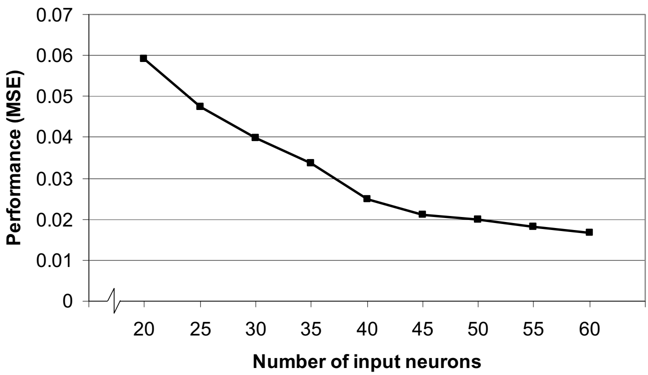

Figure 5.6: Residual error after training w.r.t. the number of input neurons

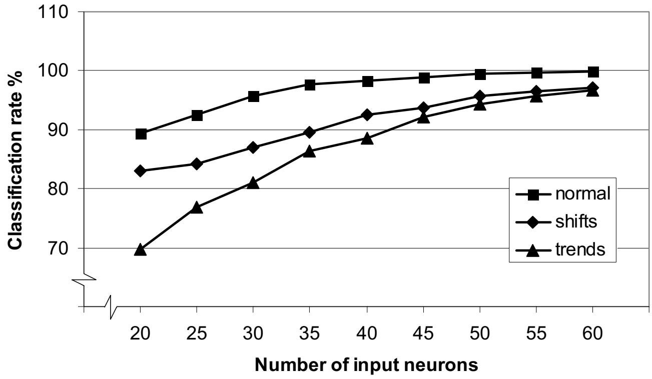

Figure 5.7: Classification rate w.r.t. the number of input neurons

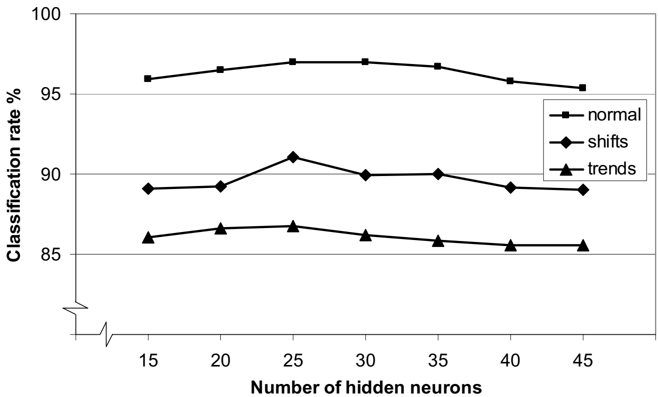

Figure 5.8: Classification rate w.r.t. the number of hidden neurons

<u>Output neurons activation function</u>

Although the network output is limited to [0, 1], numerical results showed that the linear activation function for the output neurons performed better than the logistic sigmoid function. The result coincides with previous work [BISHOP 1995, THE MATHWORKS 2007], where the linear function was proven superior with regard to output neuron saturation problems.

Training goal and minimum error

To speed up the training process and limit overfitting effects, a maximum epoch number of 2000 was implemented. The error curve settled approximately after 600 epochs for most cases. The minimum MSE reached was 0.022.

Truth value

The tests for the best truth value were conducted using the newly obtained numbers of input and hidden neurons, forty and twenty-five, respectively. Based on the results illustrated in Figure 5.9, a truth value of 0.3 was chosen. At higher values the performance w.r.t. error type I could be improved, while error type II is negatively affected. Using values below 0.2 or even neglecting the truth value led in some cases to unacceptable classification results, where common cause variation and process noise were more often misinterpreted.

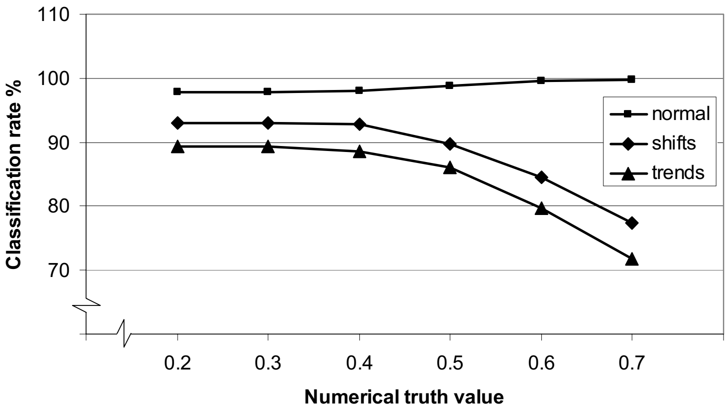

Figure 5.9: Classification rate w.r.t. the numerical truth value

5.5.1.3 Results

The optimized network parameters were tested using 6000 previously unseen test vectors representative of the five considered patterns with different deviation magnitudes. The test set contained an equal number of simulated and real data vectors. The pattern coding scheme implemented in the test set is given in Table 5.5. The codes refer to the desired NN output for the corresponding patterns. Table 5.6 presents the simulation results obtained from simulations, where the average training MSE was 0.029. The table can be interpreted as follows. For example, from all test vectors containing upward shift patterns, 92% were identified correctly. For the same pattern 2.6% were identified as normal process behavior and thus contribute to the overall error type I. The remaining 5.4% were identified as upward trend patterns.

Table 5.5: Pattern coding

Code	Pattern	Code	Pattern
10	Normal pattern		
21	Small upward mean shift ($\Delta \leq 1\sigma$)	41	Small downward mean shift ($\Delta \leq 1\sigma$)
22	Small medium upward mean shift ($1\sigma < \Delta \leq 1.5\sigma$)	42	Small medium downward mean shift ($1\sigma < \Delta \leq 1.5\sigma$)
23	Large medium upward mean shift ($1.5\sigma < \Delta \leq 2\sigma$)	43	Large medium downward mean shift ($1.5\sigma < \Delta \leq 2\sigma$)
24	Large upward mean shift ($2\sigma < \Delta$)	44	Large downward mean shift ($2\sigma < \Delta$)
31	Small upward trend ($\Delta \leq 1\sigma$)	51	Small downward trend ($\Delta \leq 1\sigma$)
32	Small medium upward trend ($1\sigma < \Delta \leq 1.5\sigma$)	52	Small medium downward trend ($1\sigma < \Delta \leq 1.5\sigma$)
33	Large medium upward trend ($1.5\sigma < \Delta \leq 2\sigma$)	53	Large medium downward trend ($1.5\sigma < \Delta \leq 2\sigma$)
34	Large upward trend ($2\sigma < \Delta$)	54	Large downward trend ($2\sigma < \Delta$)

Table 5.6: Final classification results of NN-11 as percentages of the number of test vectors of each fault pattern

Target output (pattern code)		percentage detected as				
		normal	Upward shift	downward shift	Upward trend	downward trend
Normal	10	**98.5**	0.35	0.2	0.4	0.55
Upward shift	21	10.4	74	0	15.6	0
	22	0	94.8	0	6	0
	23	0	99.2	0	0	0
	24	0	100	0	0	0
	Tot.	2.6	**92**	0	5.4	0
Down-ward shift	31	4.8	0	68.4	0	26.8
	32	0	0	97.2	0	2.8
	33	0	0	100	0	0
	34	0	0	100	0	0
	Tot.	1.2	0	**91.4**	0	7.4
Upward trend	41	30	16	0	54	0
	42	0	7.6	0	92.4	0
	43	0	0.4	0	99.6	0
	44	0	0	0	100	0
	Tot.	7.5	6	0	**86.5**	0
Down-ward trend	51	25.6	0	9.2	0	66
	52	0	0	3.2	0	96.8
	53	0	0	1.2	0	98.8
	54	0	0	0	0	99.2
	Tot.	6.4	0	3.4	0	**90.2**

Three categories of falsely interpreted data could be identified in the results: error type I, error type II and pattern interference. Error type I for the chosen configuration reached 1.5% and could be improved if a larger recognition window was implemented. On average, error type II among the considered fault patterns was 4.4%. Only errors in identifying samples of the lowest deviation magnitude contributed to the latter statistic. The third proportion of the falsely interpreted test samples represents pattern interferences. This effect is not critical for the detection scheme because the deviation tendency (positive or negative direction) is determined correctly, i. e. the correlation analysis would still be successful. Furthermore, the interferences were observed in the deviations with the lowest magnitude. Once the deviation reaches 1σ, the interferences decrease rapidly. The test patterns with moderate and large deviations were correctly identified at an average classification rate of 98.2%. The rule holds that the smaller the deviation from nominal, the lower the classification rate. Figure 5.10 shows the relation between the deviation magnitude and the classification rate.

Considering all deviation magnitudes and normal behavior, the overall certainty of detection is 91.7%. The result is quite acceptable, as previous investigations that reported higher classification rates involved larger shift magnitudes, reaching up to 7σ [PHAM & OZTEMEL 1994a, ZORRIASSATINE & TANNOCK 1998, GUH & TANNOCK 1999b,]. The effect of the numerical truth value can be seen in Table 5.6 as well. Less than 1% of the total number of patterns did not cross the 0.3 threshold and were interpreted as normal process behavior. All test samples failing to exceed the truth value were originally either normal behavior or trend patterns.

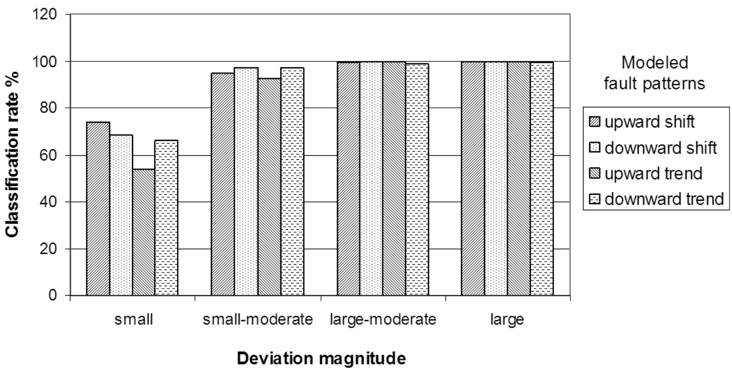

Figure 5.10: Classification rate w.r.t. the deviation magnitude

5.5.2 Step 2: Specialized classifiers (NN-121 to NN-125)

Step 2 networks serve to retest the results of NN-11 as well as to indicate the fault magnitude. The same procedure described in Section 5.5.1 was repeated to design the specialized NN in step 2. The tests led to network structures of forty, thirty and one neurons in the input, hidden and output layers of all five networks, respectively. The desired output vector was programmed such that a network outputs 0.9, if its assigned pattern is detected, and zero otherwise. The training vectors were modified to include double the quantity of large deviation vectors as before. The aim was to enhance the capability of the networks to indicate the deviation magnitude in addition to recognizing it.

Step 2 networks improved the overall classification rate of the stage to 93.2% as illustrated in Table 5.7. The table can be interpreted in the same manner as Table 5.6. Error type I could be decreased to 1%. As expected the occurrence of error type II increased slightly to 5.2%. Meanwhile, the interference between different classification categories could be reduced and contributed to the better overall performance. Similar to the results of step 1, mostly all of the incorrectly identified patterns belonged to the low magnitude deviations.

Using the five networks as an indicator of the fault magnitude proved efficient for high value deviations. However, the networks did not perform as satisfactorily in indicating low deviation magnitudes. Noteworthy is that, for an arbitrary fault case in BIW, all monitored quality characteristics deviate proportionally according to the fault pattern [CEGLAREK & SHI 1995, HU 1997], i. e. it is sufficient to consider the characteristic with the maximum deviation as an indicator of the fault severity.

Table 5.7: Final classification results of stage 1 as percentages of the number of test vectors of each fault pattern

Target output	percentage detected as				
	normal	upward shift	downward shift	upward trend	downward trend
Normal	**99**	0.2	0.05	0.45	0.3
Upward shift	4.7	**92.9**	0	2.4	0
Downward shift	4	0	**91.5**	0	4.5
Upward trend	6.2	3.2	0	**90.6**	0
Downward trend	6.1	0	1.7	0	**92.2**

5.6 Stage 2: Multivariate stage

The second stage implements a novel concept for multivariate correlation analysis. The idea is to break down the task into two parts. The first part is to detect unnatural patterns in single characteristics separately, as discussed in stage 1. The second part of the task is to compare the identified patterns in a bivariate manner and, hence, establish the relationship between the measured quality characteristics. NN are capable of assessing such behavior tendencies regardless of linearity constraints and offer a wider spectrum for applications of multivariate analysis where no exact models are available.

The analysis implemented in this stage aims at classifying the correlation patterns between the measured product characteristics into five different correlation classes: *strong positive*, *weak positive*, *strong negative*, *weak negative* and *no correlation*. The NN of the multivariate stage monitor two quality characteristics simultaneously using the output of stage 1. Therefore, the number of input neurons in NN-21 and NN-22 is double that of the output signals of stage 1, i. e. ten neurons. Based on simulation results, the number of hidden neurons for both networks was chosen to be twenty. Figure 5.11 shows the data structure used for training the networks of stage 2. The input part of the training vector consists of the output of stage 1 w.r.t. two arbitrary quality characteristics p and q. Each of NN-21 and NN-22 has three output neurons. The first neuron signals no correlation, the second weak correlation and the third strong correlation. NN-21 is trained to recognize positive correlations only, while NN-22 is concerned with negative correlations. The combined outcome of both networks describes the dependency between characteristics p and q. In the case of conflicting results, the system assumes a state of no correlation.

Using the described training scheme, the overall recognition of correlations in unseen test data reached 94.3% on average. Worth noting is that none of the cases with shift-to-shift correlation were mistakenly identified. The designed networks outperformed the classical correlation coefficient in the simulated cases, especially where the deviation magnitudes were low. The correlation coefficient was calculated for the generated test samples after adding the noise. Then the calculated and the original correlation values were compared. The maximum calculated correlation coefficient value achieved for low and moderate shift magnitudes was 0.62. In contrast, the NN delivered stronger and more reliable indications of the presence of correlations than when calculating exact correlation coefficients of the tested cases.

The proposed NN-based multivariate analysis concept proved to be a robust alternative to correlation coefficients. It can be extended without further changes to include other patterns of linearly and nonlinearly correlating characteristics.

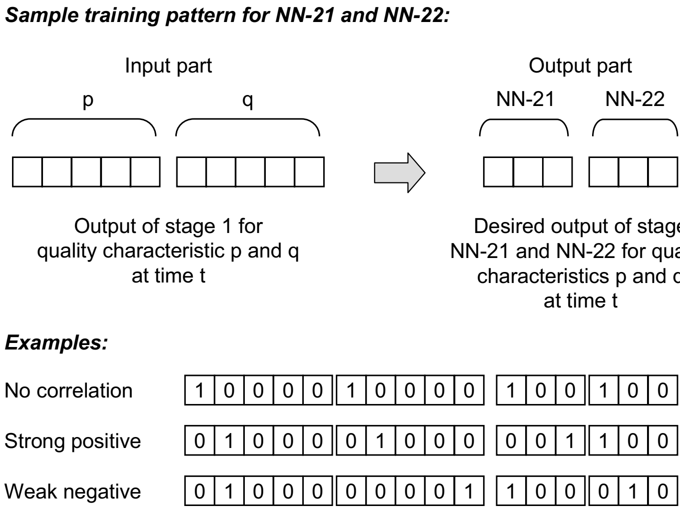

Figure 5.11: Structure of the training data of stage 2 networks and coding examples

5.7 Effect of moving recognition window

With each new product, the recognition window includes the most recent measured value and discards the oldest one. The results described up to this point do not consider this effect, as the tests consider a stationary data set. However, the fault recognition reliability is bound to increase as the system considers consecutive recognition windows. The system is given more than one opportunity to trigger alarm signals if the process is unstable, i. e. with each newly produced part having the same fault pattern. Most reported applications consider snapshot data when performing diagnostic procedures; however, real-time diagnosis requires successive snapshots of data [PRASAD & DAVIS 1993]. The example in Figure 5.12 uses real process data to illustrate the effect.

The process sequence (unseen test vector) shown in Figure 5.12 was identified as a mean shift by the production line operators. The same sequence, when introduced to the two-stage classifier, triggers a normal behavior signal starting by *window 1* up to the twelfth following part. At *window 2* and the following recognition windows, the system triggers an upward trend signal. Starting at *window 3*, the system triggers an upward shift signal. The identification of the three patterns was consistent for all intermediate recognition windows, except for two instances in the upward trend region and one instance in the upward shift region. The shift magnitude is marked by the thick horizontal lines in the figure. This is a typical fault scenario in BIW assembly and explains how the classification rate should improve greatly when consecutive measurements are taken into account.

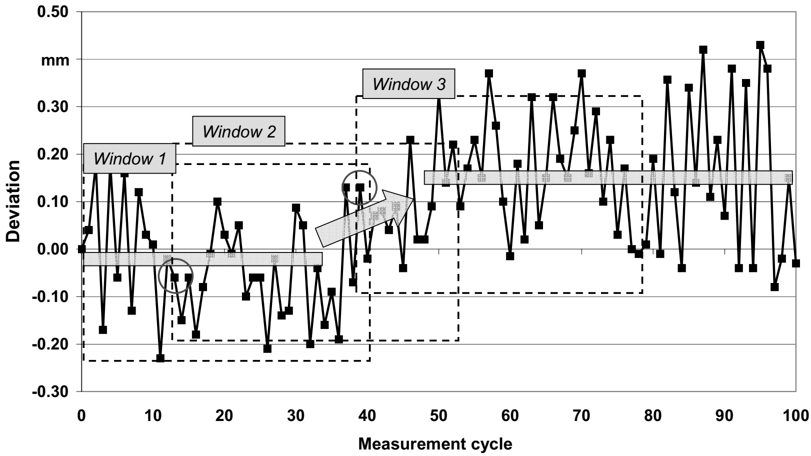

Figure 5.12: Effect of the moving recognition window on detecting a mean shift (shown sample is obtained from door production data)

5.8 Conclusion

The chapter presented a generic two-stage NN-based recognition module for monitoring production processes. The first stage is a two-step classifier for detecting trends and shifts in single quality characteristics. The second stage is a correlation observer dealing with the multivariate aspect of the monitoring task. The module receives the measured quality characteristics from the quality inspection station. The first task is to examine each quality characteristic if it contains unnatural patterns such as mean shifts or trends (univariate). Afterwards, the correlations between the quality characteristics are identified in a bivariariate manner. If unnatural patterns or correlations are recognized, the module issues an alarm signal. The alarm signals are repeated for each new measurement cycle, where process faults are recognized.

One contribution of the developed module is the consideration of small deviations ($\leq 1\sigma$). Faults can be readily detected before the process departs the specification boundaries in a centered production process with a C_{pk} of 1.33 or higher. Another contribution is the combination of univariate and multivariate analysis capabilities and the ability to deal with linear and nonlinear relations in subsets of the monitored product characteristics. The correlation observer performed well for the BIW example. However, its dependence on the univariate stage poses some limitations on its applicability to other cases. These limitations can be alleviated by including more fault patterns and other statistical distribution models to the univariate stage, which is possible using the same modular NN system.

The recognition module was designed to be process neutral and can be applied to a wide variety of production scenarios, regardless of the inspection strategy, whether 100% inspection or on sampling basis. The module can be seen in two perspectives: as a stand-alone monitoring tool or as a monitoring module of a comprehensive diagnosis system. HAYKIN 1999 comments that, "*in practice, neural networks cannot provide the solution by working individually. Rather, they need to be integrated into a consistent system engineering approach.*" The next chapters describe other components of such an integrated system.

6 Fault identification module

6.1 Overview and module structure

The purpose of the fault identification module is to identify possible fault root causes through comparing measured process data with stored knowledge or fault patterns. Fault identification is triggered when the fault recognition module signals instabilities in the production process. Two major aspects of the KBS architecture will be handled in this chapter: the development of a knowledge base and the design of an inference engine. Both components make up the fault identification module (Figure 6.1).

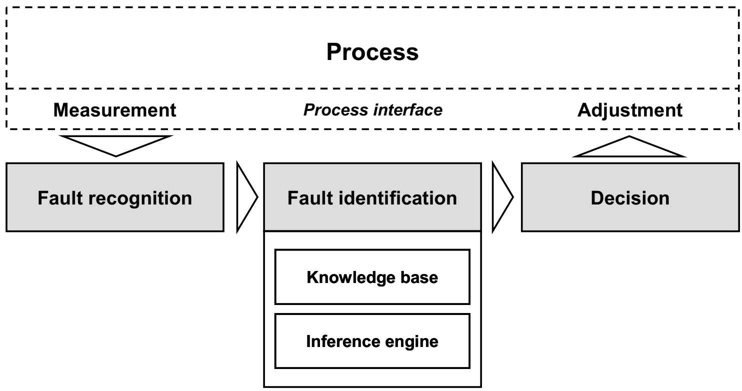

Figure 6.1: Components of the fault identification module

Knowledge representation formalizes and organizes available knowledge. One widely used technique is the production rule, which consists of an IF part known as the premise and a THEN part known as the consequent. The IF part lists a set of conditions in a given logical combination. If the premise of the rule is satisfied, the rule is said to be triggered and the consequent is executed. KBS whose knowledge is represented in rule form are called rule-based systems.

In the knowledge acquisition phase, a combination of simulation results and experience guided principles are implemented to derive the rule base. The inference engine applies fuzzy set theory to trigger consequences or actions according to the input data and the rule base structure. Fuzzy set representation is chosen to accommodate uncertainty, partial matching and input data noise. Figure 6.2 shows relevant tasks of the KBS that will be discussed next. The chapter concludes with a summary of the main results and a note on practical implementation.

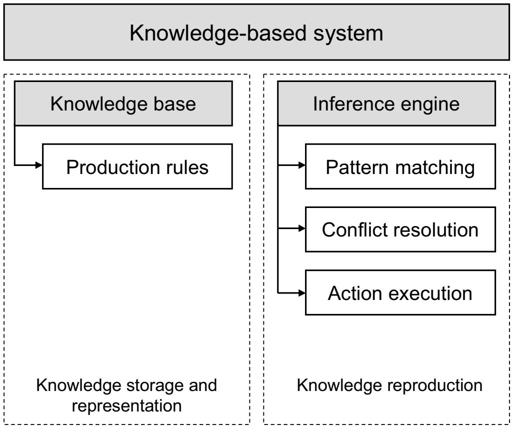

Figure 6.2: Tasks of the fault identification module in a KBS context

6.2 Knowledge acquisition

6.2.1 Procedure

The knowledge acquisition for BIW fault identification is conducted through general-purpose as well as case-specific tools that are implemented in BIW assembly design and operation phases. Using the door assembly as an example, factors affecting the dimensional integrity of the BIW product are included in the knowledge base. Figure 6.3 gives an overview of the used methods and tools.

6.2.2 General-purpose tools

Interviews, experience and documentation

In the course of the field study, several interviews and meetings were conducted with the responsible personnel in order to generate the rule base. The interviews had mostly a one-on-one character. However, in regular group meetings, one-on-many interviews were conducted as well. The interviews followed the basic semi-structured scheme [GUBRIUM & HOLSTEIN 2001], i. e. only guidelines for the discussion were prepared. Thus, the interviewee had the opportunity to express personal opinions and relate to

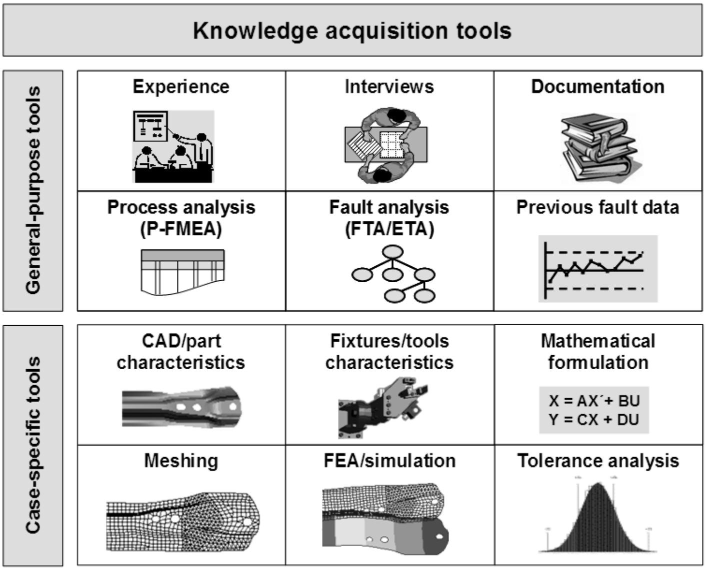

Figure 6.3: Implemented knowledge acquisition tools

similar experience where appropriate. This process extended for a year and was conducted on-site. An additional source for general rules was found in pertaining literature. Several authors addressed fine details and best-practices for modeling BIW assembly [CEGLAREK 1998, MERKLEY 1998, ADCATS 1999, HUANG et al. 2000, CEGLAREK et al. 2001, CAMELIO et al. 2003, DING et al. 2004, HUANG & SHI 2004, DING et al. 2005].

Systematic analysis of available fault reports

The analysis of previous fault cases had a two-fold purpose. The first is to obtain heuristic laws and guidelines for an extended Failure Mode and Effect Analysis (FMEA) [HERING et al. 1994, FRANKE 1989] that followed this stage. The second purpose was to formulate specific diagnostic rules for the studied production line. The relatively low granularity of the fault documentation (Table 6.1) added to the difficulty of the knowledge acquisition process.

Table 6.1: Typical granularity of BIW fault documentation (source: BMW AG)

Serial	Fault / Troubleshooting	Group	Part index	Operation index	Date
111	Weld Pts. 39423 and 39425 adjusted	TVL-E87	7069625	502A6243	15.4.2005
117	Handling Rob 4R1 substituted	TVL-E87	7069625	104A8	…
165	Side frame St. 3+7 adjusted	TVL-E87	7069625	…	…
191	Welding gun 3R1 gap adjusted	⋮	⋮	⋮	⋮
231	Clamps St. 6 beveled				
⋮	⋮				

FMEA

FMEA is a design-evaluation procedure used to identify potential failure modes and determine the effect of each on system performance [MOBLEY 1999]. This procedure formally documents standard practices, generates historical records and serves as a basis for future improvements. The FMEA procedure is a sequence of logical steps, starting with the analysis of lower-level subsystems or components. Two types of FMEA are highly relevant in manufacturing environments: design-FMEA and process-FMEA. The design-FMEA is implemented at an earlier stage than the process-FMEA. A process-FMEA examines the ways failures in manufacturing and assembly processes can affect the quality of a product or service.

FMEA comprises an analytical part and an experiential part. The analytical part determines the fault cause and the effect and relies mostly on qualitative analysis, simulations and process history. The experiential part determines the severity, risk and probability of a fault. A common method for collectively expressing these factors is the risk priority number (RPN) [FRANKE 1989, MÜLLER 2006]. The RPN is equal to the product of the three quantities S, fault severity, O, fault likelihood, and D, fault detectability, each estimated on a scale of ten (Equation 6.1).

$$\mathrm{RPN} = \mathrm{S} \cdot \mathrm{O} \cdot \mathrm{D} \tag{6.1}$$

Fault tree analysis/Event tree Analysis (FTA/ETA)

FTA is a top-down technique for assessing the way in which several failures can cause a single outcome or a system failure [BAYDAR & SAITOU 2001]. It is different from FMEA in that it is restricted to identifying system elements and events that lead to one particular undesired event. ETA is a forward technique, which may be used to examine the propagation of an initiating event with the presence of a number of other events, faults or conditions. FTA and ETA may be applied during the design stage of the assembly system in order to predict possible propagated failure situations [BAYDAR & SAITOU 2001]. Thus, they provide an objective basis for justifying system changes, performing trade-off studies and demonstrating compliance with safety and environment requirements. The analogy between the build sequence of the assembly process and the FTA is established in the next section and is used later to construct the rule hierarchy.

6.2.3 Case-specific tools

Hierarchical representation and diagnosability levels of the assembly process

An intuitive way to capture fault knowledge in assembly is to use a hierarchical representation of the assembly process. In many cases such a representation is equivalent to the assembly precedence graph. Using the door assembly as an example, the tree-shaped hierarchy in Figure 6.4 represents the build sequence. The hierarchical representation is helpful since it offers a unified framework for representing knowledge of different fault types: assembly fixture related, welding gun related, stamped part related and material handling related. Clusters of fault sources can be assigned to each assembly operation in any of the hierarchy levels. The hierarchy also reflects a possible structure of the rule base, where the rules can be categorized into levels analogous to those of the assembly sequence. For example, in Figure 6.4 the fault specification level generally increases moving top down.

Another critical notion in this context is that of diagnosability. If there is one and only one root cause for any given fault, the assembly is called fully diagnosable. Otherwise, the assembly is non-diagnosable [DANAI & CHIN 1991]. HU 1997 concludes that in order to achieve full diagnosability in serial assembly, the number of measurement points must be equal to or higher than the number of variation sources. He further states that parallel assemblies are not fully diagnosable no matter how many measurement points are used. One common practice is to differentiate between station-wise and element-wise diagnosability, as suggested by CARLSON & SÖDERBERG 2003 and DING et al. 2002c. An example in DING et al. 2002c shows that in-process sensing involving fewer measurement points is generally capable of higher diagnosability than EOL sensing in multistation manufacturing processes. The disadvantage, however, is the technical and economic feasibility of the additional measurement stations.

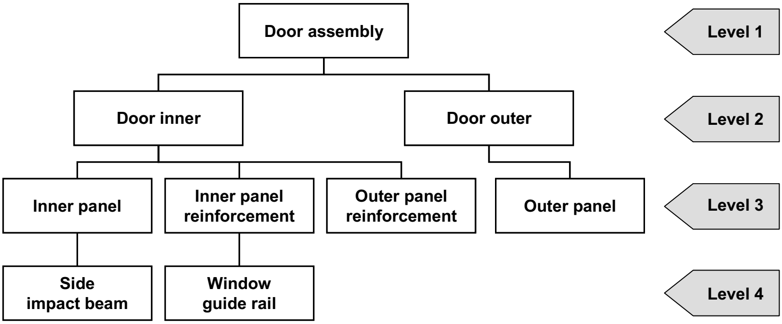

Figure 6.4: Hierarchical levels of the door assembly (after [CEGLAREK & SHI 1995])

Tolerance analysis

Modern practices in tolerance analysis expand the standard definition of tolerancing, which bounded error contributors to product variables only, to explicitly include process variables [DING et al. 2005]. In the same line, the concept of process interchangeability replaces gradually the conventionally implemented part interchangeability. Figure 6.5 illustrates the effect of a locator (process parameter) dimensional error on the part quality.

The results of statistical tolerance analyses from the design phase of the vehicle were studied in order to document the tendencies of the quality deviations (fault patterns) associated with certain root causes, and not the exact calculation of tolerance chains. Further information regarding the process interchangeability could also be generated for rigid panels using CAD and for non-rigid panels using FEA.

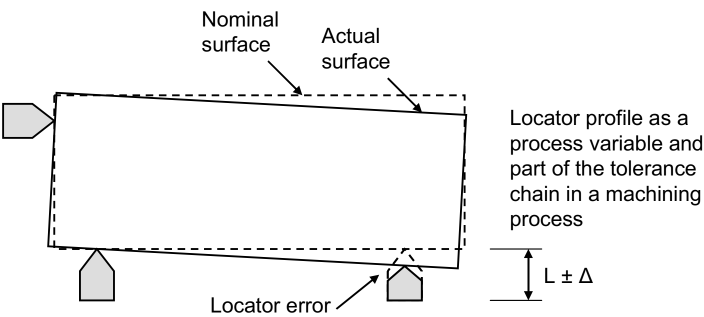

Figure 6.5: The effect of process variables on product quality [Ding et al. 2005]

CAD as a simulation tool for rigid body fixturing errors

In the cases where the assembled parts can be considered rigid, simple simulations can be conducted in the CAD environment to determine the fault effect quantitatively. The technique is straight forward and can be mathematically described through basic trigonometry. It can be seen as a simplified form of the tolerance analysis. Such an analysis considers the sheet metal parts and the process features at the same time. However, non-rigid parts are assembled in 37% of the BIW stations [SHIU et al. 1997]. In such situations, qualitative results can be reached. The simulation is similar to the rigid body movement due to the locator error in Figure 6.5.

Numerical modeling using finite element analysis (FEA)

Numerical methods using FEA can be used to develop variation simulation models for deformable sheet metal parts with complex 3D free form surfaces [LIU 1995]. Recently, sensitivity analysis techniques, e. g. the influence coefficients method, replaced the time consuming Monte Carlo simulations in FEA fault modeling. Other approaches suggest applying PCA additionally to limit the search space [CAMELIO et al. 2004]. Using FEA, it is possible to address issues of spring back and part deformation and their effects on the assembly dimensional integrity [LIU & HU 1997].

The level of detail of the FEA is a matter of concern. On one hand, it should be as low as possible for an economic design of the KBS. On the other hand it should capture the modeled faults with sufficient accuracy. For the intended KBS application, the FEA results should deliver the correct tendencies of the fault pattern, but an exact estimation of the deformations is not required. An example illustrating the use of simplified boundary conditions is given in Section 6.2.4.2. Recent FEA applications can deliver results of higher accuracy that exceed the needed level for the KBS at hand [MERKLEY 1998, BIHLMAIER 1999, VON PRAUN 2003, CAMELIO et al. 2004, ZAEH et al. 2006]. The boundary conditions are obtained from process documents and models (e. g. eM-Workplace®). Simulations of the flexible assembly parts were conducted using Hypermesh® and Patran®/Nastran®. Moreover, the uncertainty of the results is compensated for by the inference engine.

6.2.4 Results

6.2.4.1 General diagnostics

The following list presents some important features of the BIW assembly that are implementable as general diagnostic rules. These general diagnostic rules may also be regarded as metarules [RAUMA 1997, JACKSON 1999, MAQBOOL et al. 2005] that guide the use and the priority of case-specific rules. They can be projected on a known assembly configuration to generate case-specific rules, i. e. use common knowledge to generate specific knowledge. Where due, reference is made to literature containing similar results.

- Process configuration, number and locations of the spot welds and fixtures affect the assembly variation (also in LIU 1995).
- In-plane faults (e. g. gaps) are often caused by locators or fixtures. Welding guns, clamps or part faults cause out-of-plane faults (e. g. flush). In both cases, correlations are observed.
- Key contributors to the final fault pattern in BIW assembly include the tooling error, part accumulative error and reorientation error along the propagation path (also in JIN & SHI 1999).
- The stiffness of a parallel assembly increases while the variability of the resultant dimension decreases. The stiffness of a serial assembly decreases while the variability of the resultant dimension increases [HU 1997].
- The behavior of stiffer parts is dominant in determining the overall assembly variation [LIU 1995].
- Assembly operations tend to reduce the mean shifts but increase the variation.
- A direct relation exists between the shear forces provided by the weld nuggets and springback [LIU 1995].
- Lap joints absorb assembly variation and offer lower risk of fault propagation than butt joints, i. e. butt joints are more likely to be a fault source.
- Stations where simultaneous welding takes place are less likely to contribute to the overall dimensional variation. Sequential welding results in higher variation.
- Welding from strong to weak results in higher variation. Stations with this configuration are more likely to be fault sources.
- If the measured values indicate correlated deviations, then the probability of a single fault source is higher. If the measurements are uncorrelated, then they have different root causes [CEGLAREK & SHI 1995]. In contrast, CARLSON & SÖDERBERG 2003 assume that multiple but uncoupled locator errors occur. The field study (Chapter 3) confirmed the former postulation.
- Tailor-welded blanks have lower variation levels than normal blanks.
- Faults occur more frequently after cold starts. The stamped parts in storage or in nests cool down and contract causing deviations (e. g. outliers). The same effect takes place after temporary shut-downs.

- In the warm-up phase of assembly robots, trends in the mean values of the quality characteristics are to be expected. If temperature drift compensation is applied, a saw-tooth behavior is usually observed.
- If all measurement points (MP) *move* together with the same amplitude and direction, the principal locating panel (e. g. the door inner panel) or the coordinate transformation matrices should be checked.
- Outliers falsify calculated correlation coefficients drastically.
- Practically, assemblies are non-fully diagnosable. The best station-level diagnosability is the primary target followed by the diagnosis on locator level.

The door assembly is dominantly parallel in nature. The hanging strategy of the door compensates for gap errors but not for flushness errors. Hence, the critical fault root causes relate to flushness, as reflected by the measurement scheme. Mixed contact positioning[19] prevails in the assembly process. Reorientation effects on the fault pattern in the case of the door are minimal because of the parallel assembly.

6.2.4.2 Case-specific diagnostics

The fault knowledge should contain information on the event (product deviation or fault pattern), the process (context of fault occurrence), the cause (deviation root cause) and the action (troubleshooting measure) [HATAMURA et al. 2003]. When describing the faults in the knowledge base, these four basic aspects are complemented by information on the frequency, probability and risk of the fault. The fault pattern is described in vector form compatible with the measurement scheme. The following examples illustrate how case-specific knowledge and diagnostic rules can be generated. At the same time, these examples represent general approaches to modeling geometrical faults in BIW.

Case 1: Fixture grouping (e. g. high variation due to clamp fault)

It is impractical to consider each locator or clamp as a fault source. Hence, it is proposed to form fixture groups that contain related elements that cause similar fault patterns. In this way, it is possible to reduce the number of variation sources in the knowledge base and yet cover a sufficient number of fault root causes. Figure 6.6 illustrates the procedure and shows the relation between a product fault and its possible root causes.

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[19] The terminology adapted from CARLSON & SÖDERBERG 2003. In mixed contact positioning one part is typically fully constrained by its fixture, while the other is constrained by both the first part and another fixture. Another possible configuration is the fixture contact positioning, where the parts to be assembled are fully constrained by their respective fixtures. Both situations are common in the automotive BIW assembly.

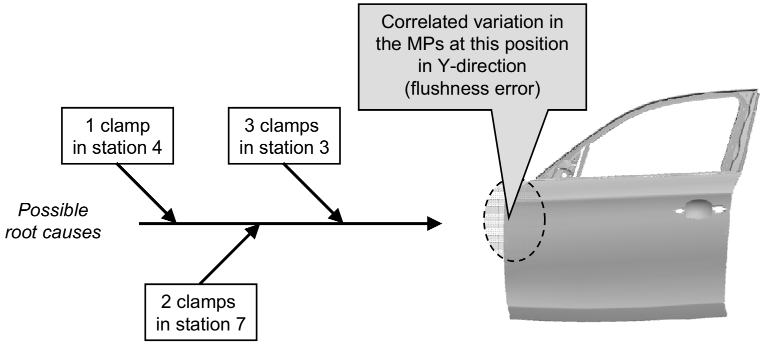

Figure 6.6: Example of possible clamp faults with similar effect on the final product

Fixture groups at the relevant assembly stations are identified and prioritized to form the diagnosis search space. Prioritization depends on the contribution of each station to the geometry and the results of statistical tolerance analysis. The aspect of prioritization is addressed in the next section and later again in terms of the inference engine and the conflict resolution strategy. The fault effect in Figure 6.6 is described as a correlated out-of-plane variation, which is typically associated with clamping force variations. The fault effect can be detected through the multivariate stage in the fault recognition module (refer to Section 5.3 and Section 5.6). With the premise of such a fault pattern, the consequent of the diagnostic rule guides the user to search in station 3 with highest priority followed by the other two possible root causes.

Case 2: Tool path tracking (e. g. mean shift due to weld gun offset)

An offset in the weld gun is a common root cause for deviations in the final product. Such a fault often leads to correlated mean shifts of the measured quality characteristics. It is generally possible to establish a relation between the tool (weld gun) path in the assembly station and the effect on the product. Referring to Figure 6.7, the weld nuggets in the upper right corner of the door are applied in stations 3 and 4, respectively. In case a fault pattern with maximum deviation at this position is detected, the diagnostic rules would indicate a root cause in station 3 with higher probability than station 4. The third priority is set to station two considering possible error accumulation and reorientation effects. Such a fault is recovered either by reprogramming the robot or adjusting the weld gun offset. As mentioned before, welding and handling robots typically serve more than one assembly station in common line configurations. Thus, the same welding gun may be associated with more than one rule in the knowledge base. The latter notion is beneficial since it allows the differentiation between robot programming errors that cause local deviations and physical damages in the weld gun that affect the whole tool path.

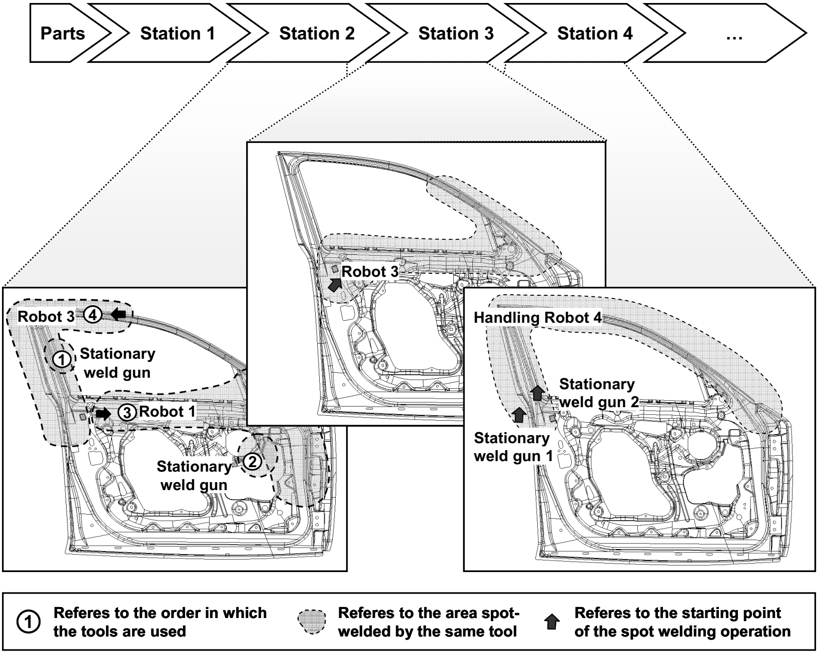

Figure 6.7: Weld robot paths as a basis for generating case-specific diagnostics

Case 3: Fault modes of large panels (e. g. bending of the door inner panel)

Large panels in BIW are susceptible to bending and twisting deformation modes that may dominate the whole assembly. The door assembly is no exception and is dominated by the deformation modes of the door inner panel, which is the main locating panel of the door. The knowledge base hence should include diagnostic rules that capture such behavior, as illustrated by the following example.

A bending deformation about the X-axis of the door may occur during the assembly process. Applying excessive torque to the assembly bolts joining the side impact beam to the door inner panel in station 7 is identified as the most significant root cause of this mode. The effect can be readily predicted through an FEA in the process planning phase. Figure 6.8 shows the results of FEA with approximated boundary conditions that led to generating a corresponding fault pattern. The values implemented for clamping and joining forces can be determined from the known pneumatic pressure of the clamps and weld guns.

The simulation in Figure 6.8 uses multiple point constraints to model the weld spots and the threaded joint. Reorientation effects on the final fault pattern are minimal because of the parallel nature of the door assembly. The result agrees with the observed fault pattern in actual measurements. FEA using approximated boundary conditions can be conducted in a similar way for other fault scenarios.

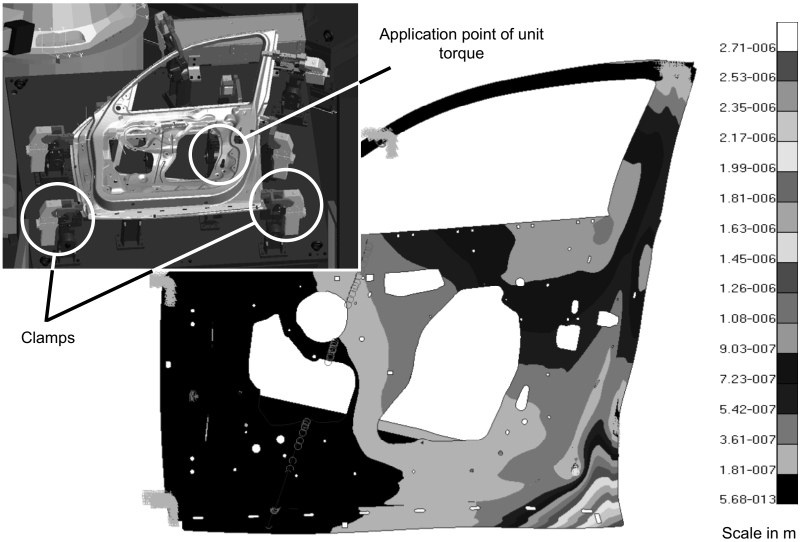

Figure 6.8: Effect of faulty process parameters during the side impact beam assembly - FEA deformation results (main figure) and boundary conditions (upper left corner)

Case 4: Single station related faults (e. g. gap deviation in window slit)

Some fault patterns can be associated with certain assembly stations with high probability. A correlated deviation in the window gap size is one such example (Figure 6.9). The fault pattern can be associated with station 6 only and is completely captured by the measurement points 2, 3, 5 and 6 (refer to the measurement scheme in Figure 3.5 on page 50). Formulating a diagnostic rule is straight forward in this case. However, it requires more analysis to identify which locator or tool is responsible for the fault. If part rigidity can be fairly assumed, 3D-CAD representations of fault cases as indicated in Section 6.2.3 may be used to predict the corresponding fault pattern.

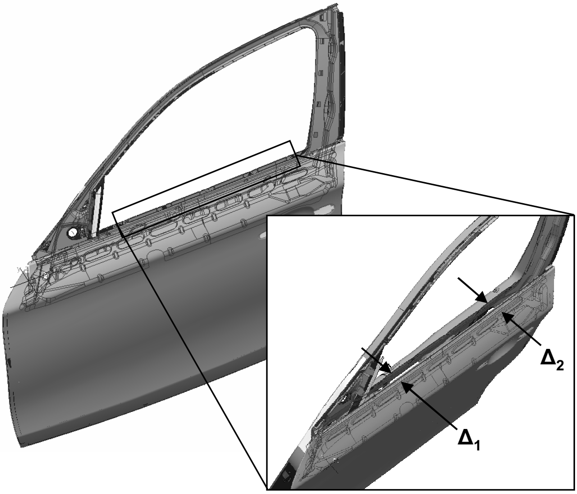

Figure 6.9: Gap deviation between the door inner and outer panels (ideally $\Delta_1 = \Delta_2$)

6.2.4.3 Representation of the results

The diagnostic rules collectively represent an abstract description of the assembly process from a fault propagation point of view. The results of the knowledge acquisition process are formulated in an adapted FMEA form, where the quantities S', O' and D' replace the conventional S, O, and D, respectively. S' represents the impact of the root cause on the fault pattern, i. e. to which extent the root cause contributes to the fault severity. O' represents the frequency of occurrence of the fault root cause. D' reflects the analysis effort and time required to establish enough certainty about the fault root cause. The three parameters are multiplied to give the adapted risk priority number (aRPN). The interpretation of the parameters S', O' and D' is summarized in Table 6.2.

Table 6.3 gives an outline how the knowledge acquisition results are documented using the developed metrics. The table includes additional information, such as the description of the fault cause and information on the recovery action. The issue of recovery cost (last column in Table 6.3) will be addressed later in the decision module (Chapter 7).

Table 6.2: Adapted FMEA parameters

Parameter	Value	Interpretation
S’	1 - 3	Root cause is an insignificant contributor to the fault pattern
	4 - 7	Root cause is a moderate contributor to the fault pattern
	8 - 10	Root cause is a major contributor to the fault pattern
O’	1 - 3	1/20000 or once every four weeks* and lower
	4 - 7	1/5000 or once a week*
	8 - 10	1/1000 or once a day* and higher
D’	1 - 3	Root cause can be identified easily
	4 - 7	Root cause can be identified with moderate effort
	8 - 10	Root cause can be identified with difficulty

* *Intervals are based on the investigated door production line*

6.3 Rule base (knowledge representation)

Rule-based systems are the most widely used form of KBS [DYM & LEVITT 1991]. A rule can be expressed as:

<Rule>: If <premise> then <consequent> (6.2)

or

<Rule>: If <attribute> satisfies <condition> then execute <action> (6.3)

Thus, the knowledge base or the rule base consists of a number of if-then rules with these basic components:

Attributes: Measurement data or quality characteristics

Conditions: Deviation categories, e. g. negative large, normal, etc.

Actions: Assigning the pattern to a modeled fault class

Rules: Diagnostic rules linking attributes, conditions and actions

Table 6.3: Door assembly diagnostics – adapted FMEA representation

Fault pattern*	Fault effect	Root cause	S'	O'	D'	aRPN	Recovery action	Recovery cost
Pattern 1	Optical (flushness), noise	Station 3, clamps 5, 7, 8 (fixture grp. 2)	6	2	4	48	Add shims, replace clamp	moderate
		Station 4, clamp 2	5	2	3	30		
		Station 7 clamps 6, 8	4	3	2	24		
Pattern 2	Optical (flush-ness/gap), noise	Station 3	7	4	6	168	Reteach robot, grind weld tips	low
		Station 4	7	3	5	105		
		Station 2	5	3	6	90		
Pattern 3	Optical (flushness), noise	Station 7, torque span-ner	8	4	2	64	Adjust spanner	low
Pattern 4	Optical (gap)	Station 6	6	2	3	36	Adjust locators	moderate
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮

* *Described in vector form*

The advantage of rule-based systems lies in the ability to combine several rules if no unique classification is possible and in the intuitive elicitation of expert knowledge. A rule base can be represented as text, as decision tables or in graphical form [GONZALEZ & DANKEL 1993]. The conditions in the rule premise represent an assessment of the product quality and are mostly communicated verbally by the human expert. Also, considering their different natures, it is convenient to describe the corrective actions in linguistic form. Fuzzy reasoning offers a suitable solution for knowledge reproduction in such a case.

For case-specific diagnostics, fuzzy representation allows inference under partial fulfillment of the rule conditions and associates each suggested action with a matching degree. The benefits extend further in the case of general diagnostics as it is very difficult to develop exact definitions for many of the classification mechanisms applied by human experts. Associating linguistic terms with fuzzy sets guarantees transferability and intuition in the application. Fuzzy rules, fuzzy inference and conflict resolution for the acquired diagnostic rules are discussed next in Section 6.4.

The rationale of the conflict resolution strategy is explained as follows. For the most part, the acquisition of specific process knowledge followed a *forward* reasoning pattern (Figure 6.10). In contrast, to build the rule base, *backward* reasoning is needed in order to infer the root cause using knowledge about the actual quality deviation or fault pattern. An inherent problem to such backward logic is diagnosability. Practically, several fault sources may lead to the same type of defect. Upon the detection of such defects, relevant diagnostic rules experience an execution conflict. Thus, a conflict resolution strategy must be defined in order to supervise the execution of simultaneously triggered rules.

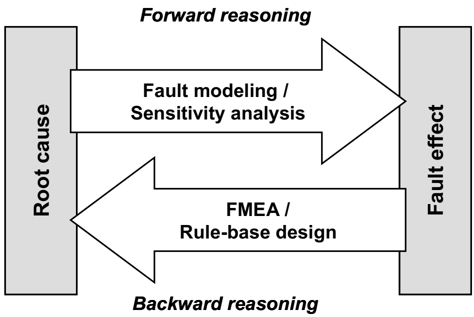

Figure 6.10: Forward versus backward reasoning in fault knowledge acquisition and representation

6.4 Inference engine (knowledge reproduction)

6.4.1 Procedure

Chaining

A powerful problem-solving paradigm is achieved by chaining of if-then rules to form a line of reasoning. If the chaining starts from a set of conditions and moves towards conclusions, the method is called forward chaining. When built into a program module, this problem-solving method is known as the inference engine. An inference engine manipulates knowledge stored in the knowledge base in order to infer actions. In forward chaining, actions are merely triggered whenever they appear on the action list of a rule whose conditions are true. This involves assigning values to attributes, evaluating conditions, and checking to see if all of the conditions in a rule are satisfied.

Fuzzy rule-based inference

Fuzzy set theory generalizes the classical set theory to allow partial membership. A fuzzy set is a set with a smooth boundary that is often associated with a linguistically meaningful term. The degree of membership in a set is expressed by a number between 0 and 1; 0 means entirely not in the set, 1 means entirely in the set, and a number in between means partially in the set. A fuzzy set is thus defined by a function that maps objects in a domain of concern to their membership values in the set. Such a function is called a membership function and is denoted μ [YEN & LANGARI 1999].

For the purpose of knowledge-based fault identification, fuzzy inference should comprise two steps in order to perform proper classification: matching and implication. Matching refers to determining the degree to which an input matches the conditions of a rule. Implication is calculating the rule's conclusion based on the matching degree. Matching and implication operations are often referred to collectively as fuzzy mapping. The input and output spaces must be partitioned before mapping can take place. The results of all rules are managed by a tailored conflict resolution strategy.

6.4.2 Fuzzy inference

Input space

The input space represents the fault pattern and hence consists of a maximum of fifteen quality characteristics as attributes in the case of monitoring the door production line. Consequently, any rule may contain up to a maximum of fifteen conditions. Figure 6.11 shows the employed input partition scheme for an arbitrary quality characteristic. The universe of discourse[20] is chosen to be the 6σ value of each quality characteristic. The partition applies triangular membership functions and satisfies the sum-to-one[21] and the closest neighbor[22] conditions [YEN & LANGARI 1999]. The partition into five categories is consistent with the design of the fault recognition module. The chosen number of descriptive terms is typical in fuzzy representations, which are rarely more than ten, rarely less than three and typically five [CHEN & HWANG 1992].The same recognition window size of forty measurement cycles (refer to Section 5.5.1.2) is

[20] The universe of discourse is the domain of interest to which the input values belong.

[21] The membership values of any possible input in all relevant fuzzy sets should sum up to unity.

[22] Each membership function overlaps only with the closest neighboring membership functions.

implemented to estimate the average deviation of each quality characteristic. The process mean values obtained in this way are fed directly to the inference engine.

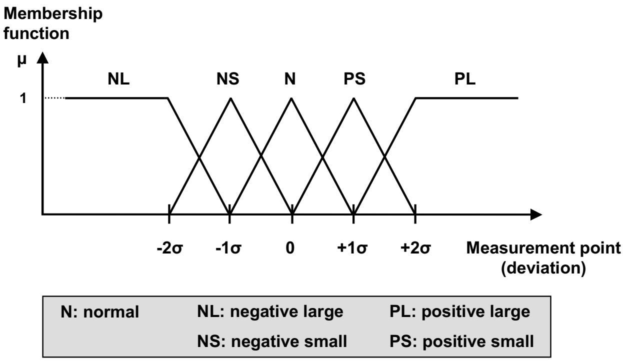

Figure 6.11: General input partition scheme for all fifteen quality characteristics

Output space

The output space describes the domain of possible rule consequents. The consequent is a linguistic statement containing information on the fault root cause, its risk priority and possible recovery actions. The form of the consequent is similar to Equation 6.4:

If <…> then fault in station 3, fixture group 1, aRPN is 64, replace clamp/add shims (6.4)

Fuzzy mapping

Fuzzy mapping determines how the input parameters and the conditions of the fuzzy rules agree. The goodness of fit is referred to as the matching degree, denoted α and often labeled the firing intensity of the rule. The set of fired fuzzy rules are prioritized according to their firing intensity.

The crisp (non-fuzzy) inputs of the inference engine are fuzzified according to the input space partition. Fuzzy operations are then implemented to calculate the matching degree of a rule's premise. Logical conjunction (AND) operations are computed using the fuzzy min-operator (Equation 6.5).

The min-operator is $$\alpha_i = \min(\mu_{i1}(a_1), \mu_{i2}(a_2), ..., \mu_{ir}(a_r)) \tag{6.5}$$

where α_i is the matching degree of the input $MP_1 = a_1$, $MP_2 = a_2$, … , $MP_r = a_r$ to the conditions of rule R_i, denoted μ_i.

Logical disjunction (OR) operations are carried out using the max-operator (Equation 6.6).

The max-operator is $\alpha_i = \max(\mu_{i1}(a_1), \mu_{i2}(a_2), ..., \mu_{ir}(a_r))$ (6.6)

The complete mapping procedure is illustrated in Figure 6.12. If different patterns are identified with the same firing intensity, the calculated aRPN is applied to set action execution priorities. The simultaneous application of both quantities α_i and aRPN aims at better exploiting the available knowledge. Fuzzy mapping is followed by the conflict resolution strategy outlined in the next section that provides the user with the final diagnostic results.

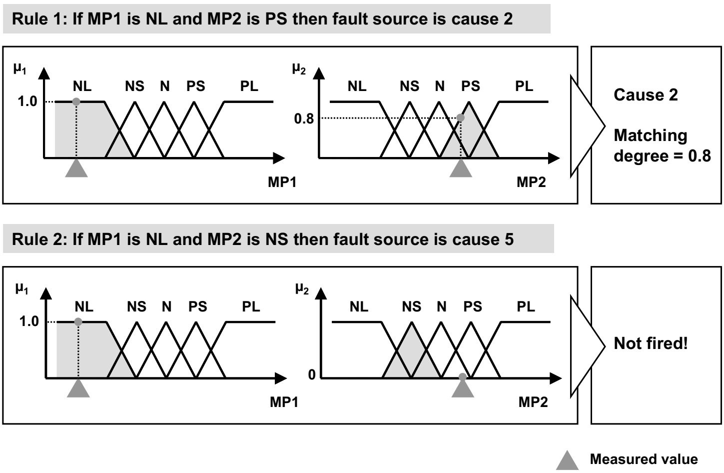

Figure 6.12: Two exemplary diagnostic rules involving two quality characteristics MP1 and MP2. The min-operator is implemented for matching and implication.

6.4.3 Conflict resolution

In order to maximize the benefit from the rule base, the rules are divided into levels corresponding to their level of specification. Based on previous discussions of diagnosability (Sections 6.2.3), the following rule levels are proposed (Figure 6.13):

Tool level: identifies a certain robot, weld gun, fixture or fixture group as the fault root cause

Station level: identifies a certain station as the fault root cause

General level: provides general instructions for recovery actions or refers the user to possible external effects, such as stamped part geometries or measurement system failure

For each input pattern, the identified action or fault class with the highest firing intensity is selected and compared to a threshold value. If the membership degree is equal to or greater than the threshold, the pattern is assigned to that class. If a pattern has equal membership degrees in different fault classes, the one with the highest risk criterion has the highest priority. If the latter is not successful, the pattern is labeled unclassified. A membership threshold of 0.5 was shown to be adequate in similar applications [YEN & LANGARI 1999]. The diagnostic strategy is summarized by the following metarules:

Metarule 1: Any rule in any level is considered fired *iff* its matching degree exceeds a threshold value of 0.5.

Metarule 2: The rules with the highest firing intensity in the highest triggered specification level are considered the most probable candidates.

Metarule 3: Cross check with fired rules from the next specification level for inconsistencies. If any, then the fault pattern is labeled unclassified.

Metarule 4: If more than one class with the same firing intensity are identified, then apply the risk priority criterion to establish action priorities.

Metarule 5: Otherwise, the fault pattern is labeled unclassified.

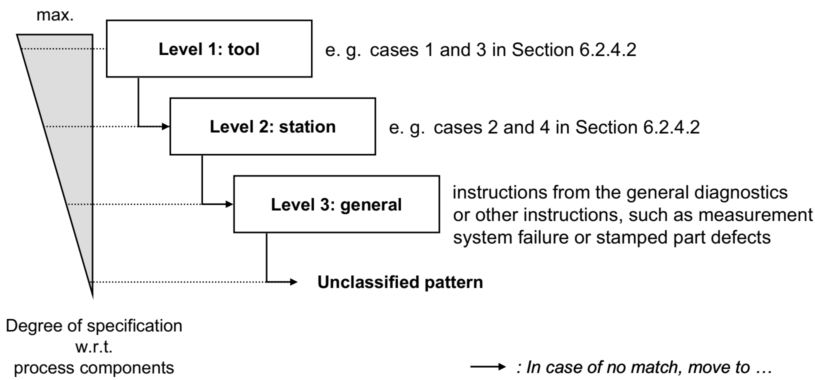

Figure 6.13: Diagnostic strategy and rule levels

6.5 Implementation and results

The rule base considered a total of seven weld stations of the door assembly line. Fourteen fixture groups were identified and assigned twenty-three rules, of which six rules indicated unique root causes. Nine rules were assigned to the weld robots and three rules to the stationary weld guns. On average, four rules and two rules were triggered for cases identified on the tool/station level and the general level, respectively. The rule base and the inference engine were validated using real process data as illustrated by the following examples.

Figure 6.14 shows a quality defect described as a flushness error in the A-pillar region. The first possible root cause, labeled cause 3 in the figure, is a fixture group involved in the assembly of the inner panel and the inner panel reinforcement. The second possible cause, labeled cause 6, refers to a fixture group in the assembly of the outer panel reinforcement and the door inner. Both root causes are equally possible according to a fault tree analysis. However, considering the risk criterion, cause 3 receives the higher priority since its contribution to the final geometry is higher. This is reflected in the equal firing intensity and the different aRPN of both root causes. In this scenario, the system delivered a total of four possible root causes after applying the conflict resolution strategy. It is clear that the lower firing intensity of causes 8 and 11 render them less favorable candidates here. The aRPN proved as an adequate criterion for enhancing the fault analysis capability. The four rules in Figure 6.14 had fifteen conditions in the premise. Generally, the more specific a rule is, the more conditions it would examine.

The previous example illustrated the use of specific rules on the tool diagnostic level. Faults due to local weld gun offset problems (e. g. when weld spot positions need to be retaught) are handled in the same manner. In the case of robot faults or a damaged weld gun, the fault pattern is associated with more than one station, which is typical to common assembly line configurations. The diagnosis of such fault cases depends on the results of the equally fired rules in the station level. The case illustrated in Figure 6.15 resulted due to faulty coordinate system settings in robot 3 serving stations 2 and 3. In the figure, cause 12 refers to station 2 and cause 14 refers to station 3, which were both triggered with the same firing intensity.

If no successful matching on the tool or the station level is achieved, general instructions are generated before declaring the input pattern unclassified. General rules would check, for example, if the deviating points are in-plane or out-of-plane. A rule is included to suggest checking consumed weld energy which correlates with the weld spot quality, in case unclassified out-of-plane deviation patterns are identified. Similarly, faulty robot temperature drift compensation which leads to wrong coordinates is also indicated as a possible root cause in the rule base.

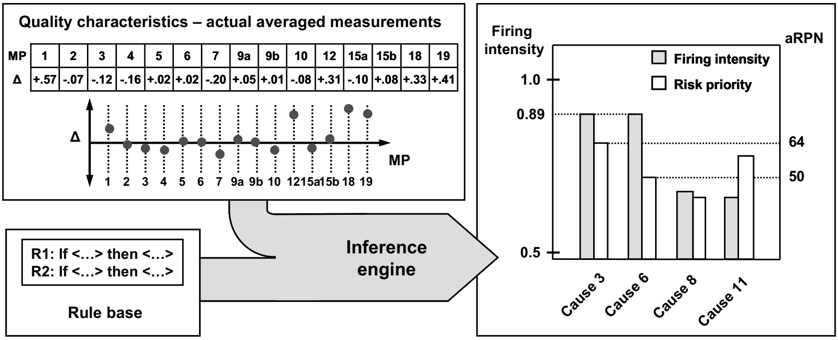

Figure 6.14: Illustrative example for the fault identification results (real process data)

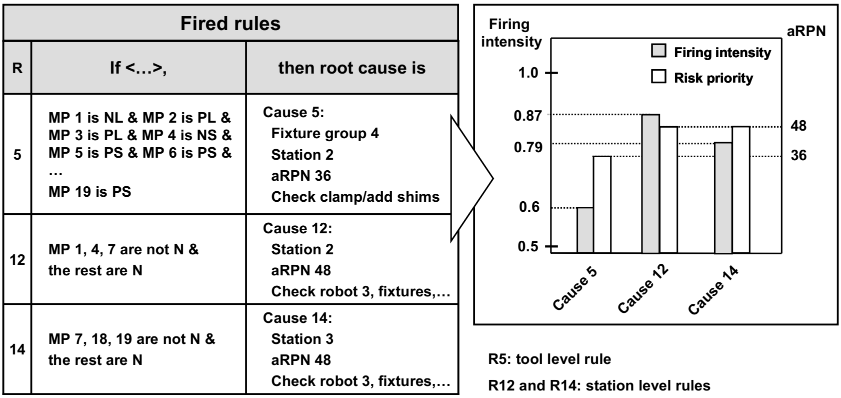

Figure 6.15: Fault case analysis using station level rules

6.6 Conclusion

The chapter introduced a rule-based fault identification system for analyzing quality defects and root causes in BIW assembly. General-purpose and specific-purpose knowledge acquisition tools were implemented to build the rule-base. The design of the fuzzy inference engine was discussed and a conflict resolution strategy was developed. For conflict resolution purposes, metarules were devised to enhance the fault isolation capability of the inference engine in addition to the combined use of the risk priority and the firing intensity criteria. Finally, the plausibility of the approach was proved using real-world test cases.

Because of its inherent flexibility and intuitive implementation, the rule-based approach proved suitable for the case of BIW assembly. However, a potential problem that demands careful knowledge management is the possible loss of overview of the rule-base. Regular checks or mechanisms should be deployed to prevent rule redundancy and keep an optimal number of rules at all times.

An advantageous point of the approach is that a rule-base can be reimplemented for similar BIW assembly lines. This notion gains further importance since manufactures always favor standardization of manufacturing procedures. Assembly lines of the same vehicle components follow an assembly scheme that is often common across different vehicle models and possibly across different manufacturers. Furthermore, process parameters may be included in the rule premise in addition to the product characteristics. As such, the capabilities of the proposed fault identification module can be extended to match an online supervisory control system that reacts to product faults.

At this point, the fault recognition and the fault identification tasks have been addressed. The following step, as described in Chapter 4, is to formulate the decision, if the process will be stopped and adjusted. The decision is governed by the statistical and the economical considerations that are associated with the identified fault case. Methods for quantifying both aspects are presented in the next chapter.

7 Decision module

7.1 Overview and module structure

The two previous modules handled the recognition of process instabilities and the investigation of their root causes. This information is indeed helpful to the quality practitioner, but not sufficient to make a decision whether to interrupt the process immediately or to allow further production. The module described in this chapter is, hence, labeled *decision*. The module proposes modeling the knowledge necessary for the latter task by means of two criteria. A statistical criterion examines the probability of the identified fault and a cost criterion estimates whether it is economical to continue production with the current deviation or to adjust the process (Figure 7.1). Only if both criteria are fulfilled, a recovery action is recommended by the diagnostic system. An illustration of the underlying theoretical background and implementation is included in the following sections. Practical examples demonstrating the validity of each component are presented. A discussion of the results concludes the chapter.

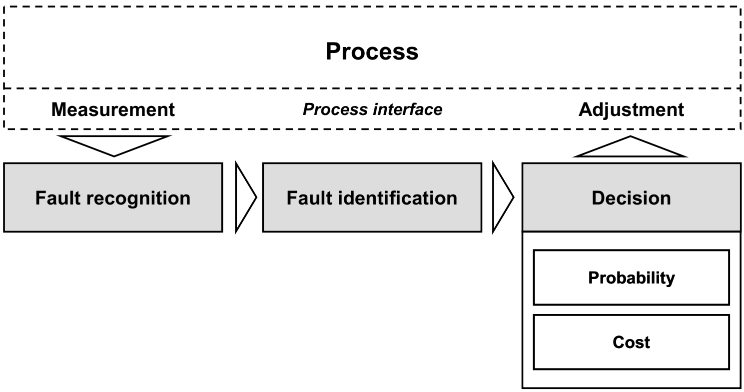

Figure 7.1: Components of the decision module

7.2 Fault probability criterion

7.2.1 Objective of fault probability consideration

If the value of a quality characteristic lies outside the allowed tolerance, the product is sorted out and either scrapped or reworked. A quality practitioner would not adjust the process then unless it is plausible to believe the fault is due to an assigned root cause and not just due to common cause variation or an outlier. Doing so, he measures the fault likelihood against a subjective threshold according to his experience. The fault probability criterion subjects the alarm signals from the fault recognition module to the same statistical analysis the human expert naturally conducts. The analysis is known in the literature as probabilistic reasoning [ROLSTON 1988, SACHS 2004]. Bayesian statistics stand as a widely accepted area in probabilistic reasoning for applications involving subjective postulations [GELMAN et al. 2004].

7.2.2 Bayes' Theorem

Bayes' Theorem implements a postulated a priori probability (subjective knowledge) of an event to infer the a posteriori probability of a dependant event [GELMAN et al. 2004, SACHS 2004]. Thus, the theorem makes use of available sample data (objective knowledge) to dynamically update the required conditional probability. Bayes' Theorem can be generally formulated as in Equation 7.1:

$$P(A_i \mid B_j) = \frac{P(B_j \mid A_i)\, P(A_i)}{\sum_i P(B_j \mid A_i)\, P(A_i)} \tag{7.1}$$

where

A_i	states of nature (possible, mutually exclusive, underlying events)
B_j	observable events (possible, mutually exclusive)
$P(A_i)$	a priori probabilities (unconditional probabilities also known as priors, i. e. before observing an event B_j)
$P(B_j \mid A_i)$	likelihoods (conditional probabilities of each observable event given each state of nature)
$P(A_i \mid B_j)$	a posteriori probabilities (i. e. after observing an event B_j, also known as posteriors)
$\sum_i P(B_j \mid A_i)\, P(A_i)$	marginal likelihood

The marginal likelihood is a normalizing constant that ensures the posterior adds up to unity; it can be computed by summing up the numerator over all possible values of A. Accordingly, the posterior can be expressed in a simpler form as given by Equation 7.2:

$$\text{Posterior} = \frac{\text{Likelihood} * \text{Prior}}{\text{Marginal likelihood}} \tag{7.2}$$

Thus, the idea is to use the qualitative information of a process evaluator to form a prior distribution and the statistical information of an outcome evaluator to update the prior and obtain a posterior distribution [VANDE VATE 1982]. The Bayesian approach in statistics has many advantages, especially in sequential applications, such as production processes [SACHS et al. 1995]. One advantage is that it elicits the assumptions for the parameter of interest from the user by having him explicitly specify the prior distribution for the parameter. The value of probability is recalculated each time using the previous posterior as the new prior [GELMAN et al. 2004].

7.2.3 Implementation

Given that an alarm is signaled, the a posteriori probability of a fault occurring in the production line P(F | A) is given by Equation 7.3.

$$P(F \mid A) = \frac{P(A \mid F)\, P(F)}{P(A \mid F)\, P(F) + P(A \mid \sim F) P(\sim F)} \tag{7.3}$$

where A is the event of an alarm signal being issued by the fault recognition module and F is the state that an assigned cause of the detected instability exists. P(F | A) represents the required conditional probability of an unstable process. ~F is equivalent to $(1-F)$ and is read “not F”.

P(A | F) stands for the probability of recognizing a fault, given that it actually exists. Its value depends on the monitoring system characteristics and is obtained from the results of the fault recognition module. The average classification rate of the univariate stage was 93.2% (refer to Section 5.5.2). Accordingly, the value of P(A | F) is 0.932. P(A | ~F) represents the probability of alarm, given a normally running process. In other words, it is equal to the type I error or the false alarm rate. Referring to the results of the first module, its value is 0.01.

The remaining critical parameter is the prior P(F). The prior is a quantification of the expert knowledge on the probability that a certain fault occurs in a known setting. For instance, in the case of the door assembly, the field study showed that the assembly line is adjusted two to five times per week. Considering a five-day week and 700 doors per day, an overall prior fault probability of 0.001 can be safely assumed, with no regard to the nature of fault. Figure 7.2 shows the result of updating the a posteriori fault probability given that successive alarm signals are issued. The figure suggests that one alarm signal is not a sufficient proof of process instability. However, if the alarm signal is repeated, the probability of a fault increases rapidly. Due to the relatively good fault recognition capabilities achieved in the fault recognition module, errors in predicting the prior P(F) have negligible effect on the posterior. With lower values of priors, a higher number of alarm signals is needed to infer statistical plausibility of a recovery action.

The probability criterion is considered to be fulfilled if and only if a predefined threshold value is exceeded. A threshold value of 80% was suggested in the literature for this purpose [BAYDAR & SAITOU 2001]. The alarm signal counter may also consider a defined production interval and not only strictly successive alarm signals. For example, for P(F) of 0.0001, three alarm signals are enough to exceed 80% posterior probability. The counter can be programmed in this case to consider three alarm signals within the last five measurement cycles as successive.

The a priori probability can be determined for each fault category separately, and thus attains much lower values than the overall prior. The values can be obtained from process history or through FMEA, tolerance analysis studies and simulations. The result is related to the estimated fault occurrence probability (O’) in the adapted FMEA (refer to Section 6.2.4.3). If the effect of the prior is low, as in the case at hand, an exact estimation of the prior is not required. A further positive aspect of Bayes’ Theorem is that the designer and the terminal decision maker may have different prior beliefs corresponding to their different experiential rules. The theorem gives space for such discrepancies and simply updates the available rule with the new postulation.

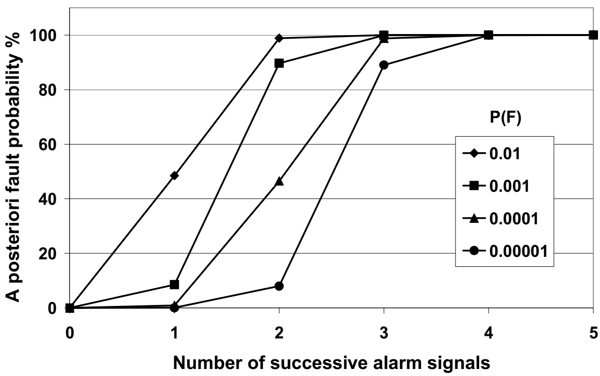

Figure 7.2: Relationship between postulated a priori probability and the calculated a posteriori of an arbitrary fault case

7.3 Recovery cost criterion

7.3.1 Objective of recovery cost consideration

Quality control schemes such as SPC do not include the production costs in the assessment of process stability [GUH & O'BRIEN 1999]. However, in many cases, the observed deterioration in product quality does not justify a corrective action. Given that a fault in the production process is identified, the quality engineer will still want to consult the process economics before deciding on a recovery action. The basic concept here is to compare the loss incurred due to a quality defect (magnitude and development of the deviation) to the cost of prevention or recovery at the instant of fault recognition. In batch production, the batch size would be a governing factor for the decision. Thus, the decision would be whether to immediately adjust the process or to complete the running batch and then adjust the process. Similarly, in series production, the maintenance schedule plays the same role.

The following section attempts to construct a theoretical model for the described trade-off. Using available knowledge and current process measurements, the model delivers a recommendation to the user. A quantification of the available quality margin for the latter case is also provided.

7.3.2 Theoretical background

7.3.2.1 Prevention-appraisal-failure (PAF) quality cost model

Quality related expenditures are probably the most controllable within the whole production budget [JURAN & GYRNA 1988] and pose a large savings potential if wisely allocated. Figure 7.3 gives a simplified overview of the elements of production costs [TAYLOR 1989]. Operating costs of quality are divided into prevention, appraisal and failure costs, also known as PAF. The three highlighted blocks in the diagram represent the two sides of the aforementioned trade-off: prevention and appraisal costs being on one side and internal failure costs being on the other. A notional representation of the three components was given in Figure 2.9. PAF costs do not include a quantification of quality deterioration. Taguchi’s QLF presents a complementary approach covering the latter deficit.

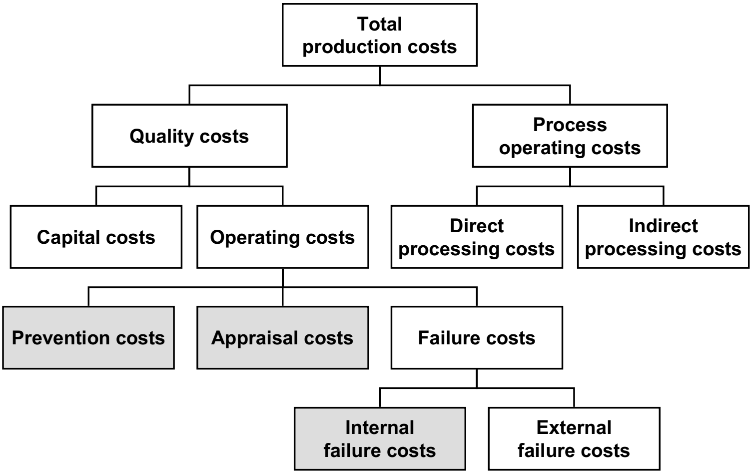

Figure 7.3: Simplified overview of the production cost elements

7.3.2.2 Taguchi's quality loss function (QLF)

Taguchi defines: "*quality is the loss a product causes to society after being shipped, other than any losses caused by its intrinsic functions*" [TAGUCHI et al. 1989]. The society in the loss concept of Taguchi includes manufacturers, customers, environment, and all others who come directly or indirectly in contact with the product. In this sense, Taguchi does not adhere to defining quality as conformance to requirements [JOSEPH 2004] and quantifies the deviations from requirements in terms of monetary units by using the quadratic loss function given by Equation 7.4:

$$L(y) = k(m - y)^2 \tag{7.4}$$

where L is the quality loss at value y, y is the current (averaged) value of a nominal-the-best quality characteristic and m its target value. k is a constant relating the deviation from target to cost. Compared to the conventional goalpost approach (Figure 7.4), Taguchi combines specifications, target value, deviation, and economy into one package to measure quality. The QLF has been extensively used for evaluating quality improvements in planning phases for the design or the adjustment tolerance limits [CAMPANELLA 1990, PEACE 1993, ROSS 1995]. However, online applications of the approach rarely exist.

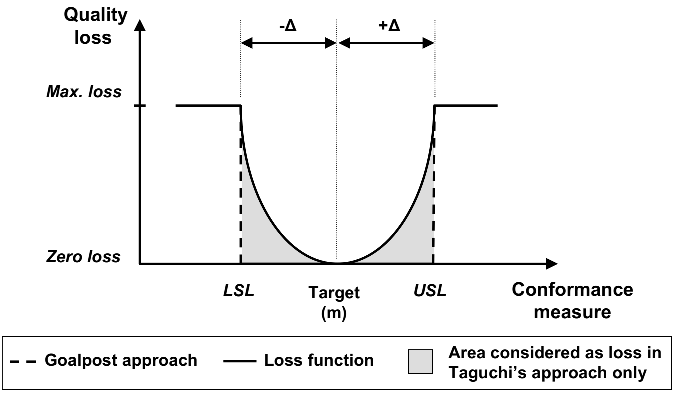

Figure 7.4: Taguchi loss function versus goalpost approach

7.3.3 Proposed online quality cost assessment

Figure 7.5 characterizes qualitatively the cost aspects in case of a fault instance. The upper two diagrams represent changes in the PAF costs while the lower diagram describes the lost quality in monetary terms following Taguchi's definition. If a fault occurs, the quality of the product deteriorates and the quality loss increases accordingly. At the same time, the operative costs increase as more rework is incorporated in the production process (higher slope in the uppermost diagram). If the fault severity is too high to tolerate, the process is stopped and adjusted. The latter recovery cost manifests itself as an increase in the average product cost and a parallel decrease in the quality loss. The cycle (T) in the figure is defined as the time period in product units from the beginning of the production - or after an adjustment - to the elimination of the assignable root cause [NAYEBPOUR & WOODALL 1993].

The proposed approach for online cost assessment (Figure 7.6) combines PAF and Taguchi cost models to determine a break-even point (BEP) between the process adjustment costs and the quality loss per produced part. The process is assumed to exhibit a systematic fault while still within the specification limits, e. g. a shift in the process mean. Costs due to fault detection lag are neglected under the assumption of 100% inspection. Nominal-the-best features are considered. Also, the generalization of the trade-off to larger-the-better and smaller-the-better features is straight forward. Clearly, if the specification limit is exceeded, there is no need for conducting such a trade-off as the process will be stopped immediately.

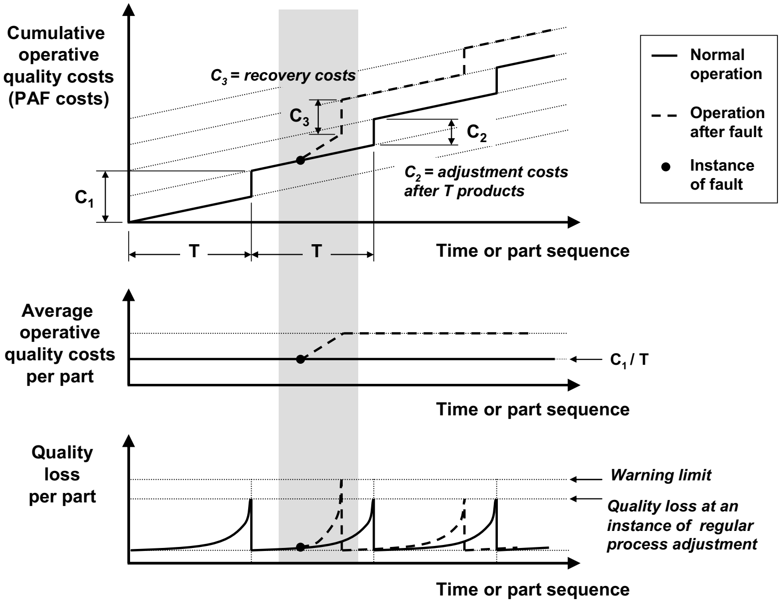

Figure 7.5: Quality costs at the instance of a fault

In Figure 7.6, the quality loss C_a (curve 1) is modeled as a quadratic function as given by Equation 7.5:

$$C_a = \frac{C_{a,max}}{\Delta^2}(y-m)^2 \tag{7.5}$$

The quality loss is zero when the process is on target (m) and increases quadratically with the deviation magnitude (y-m). The loss reaches a maximum ($C_{a,max}$) at the specification limit (m+Δ), which corresponds to the cost of rework or scrap. The curve thus accounts for expected losses in downstream operations due to an off-target process mean. The fault pattern affects the value of the quality loss, while the cost of process adjustment depends on the fault root cause identified. The amount of process deviation observed affects both quantities.

The process adjustment costs C_b (curve 2) are modeled as a linear function of the deviation (y-m) as given by Equation 7.6:

$$C_b = C_{b1} + \frac{C_{b2}}{\Delta}(y-m) \tag{7.6}$$

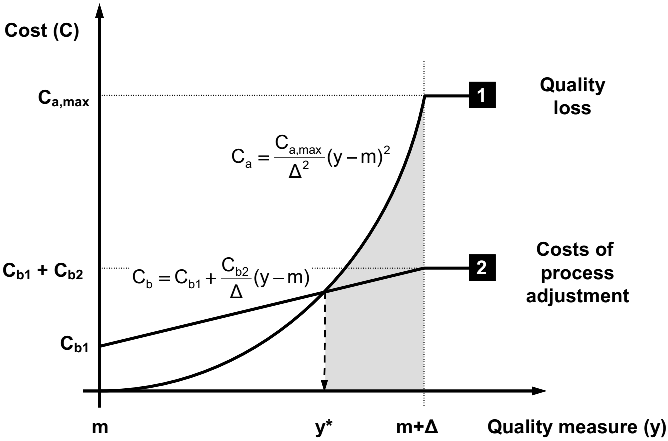

Figure 7.6: Concept of online quality cost assessment

The assumption of linearity is fairly plausible considering the following two cost components. The direct recovery cost C_{b1} is a constant part that relates to basic repair and maintenance activities, such as replacement through spare parts (hardware) or adjusting control parameters (software). The second cost component reaches a maximum of C_{b2} at the specification limit (m+Δ) and refers to the cost incurred due to process interruption during recovery under the assumption that larger deviations demand more adjustment time. The variable part also accounts for the shorter process run due to the fault instance.

Both cost components are readily known if the root cause has been identified. This information is obtained from the knowledge base and the inference results (Table 6.3). The estimated fault frequency is used to determine the value of the adjustment cost per produced item. In case that the fault can not be identified, it is proposed to implement a constant value for C_b, which depends on the interval and the cost of regular process adjustments.

7.3.4 Validation and implementation

The following examples illustrate the implementation and the validity of the proposed cost model. Data obtained from literature and from the production facility was used for this purpose. The term *process* in the illustrated examples refers to an arbitrary quality characteristic, which exhibited deviation from normal operation conditions.

Example 1

The data for this example was obtained from the car seat assembly line described in TSOU & CHEN 2005. The process is symmetrically toleranced with specification 402 ± 2 mm. The estimated run between adjustments is 5000 parts. Cost of process adjustment is 200 $, which corresponds to the adjustment of the car seat frame assembly fixture. The fault considered here is a deviation of the hole-to-hole distance necessary for installing the seat in the vehicle. Rework cost is given at 1 $ per part.

The problem data summarized in Table 7.2 is used to construct the cost model. The term *run* refers to the expected number of parts between two fault instances. The target is to determine the BEP (y*) and act accordingly in case systematic deviation is observed. The variable recovery cost component is considered as 10% of the fixed component at maximum deviation. This is a conservative value since no explicit value is available. Hence, the BEP is found at 0.404 mm. Knowing that the process ran normally at a C_{pk} of 1.47, the calculated BEP suggests that at a process drift of 1σ or higher, it is recommended to stop and correct the fault. The result compares well to the recommendations of the authors, where a similar value was reported as an optimal balance between production costs and quality investment. In Figure 7.7, sample 1 lies within the acceptable region, left of the BEP, while sample 2 is on the opposite side. The decision in the latter case falls on an immediate recovery action.

Table 7.1: Input data for the quality cost trade-off of example 1

Parameter	Value	Parameter	Value
Run	5000 parts	LSL	400 mm
Target	402 mm	Rework cost	1 $/part
USL	404 mm	Recovery cost	200 $

Example 2

This example is based on the process described in GUH & O'BRIEN 1999 and originally published in MONTGOMERY 1980. The investigated characteristic is the inside diameter of piston rings in a forging process. Table 7.2 summarizes the process data. The variable recovery cost component is 10% of the fixed component at maximum deviation. Applying the postulated cost model, a BEP is found at 74.0049 mm, which corresponds to a mean shift of 0.0048 mm. Hence, a mean shift with the latter value is high enough to adjust the process. In the described application, the process ran at σ of 0.0044 mm. Similar to the previous example, the critical process deviation is approximately 1σ away from the target. The achieved result agrees with the authors' assumption of a normal variation level of 1σ. The proposed cost model was capable of capturing the process economics and providing a quantification of the impact of quality variation on process costs.

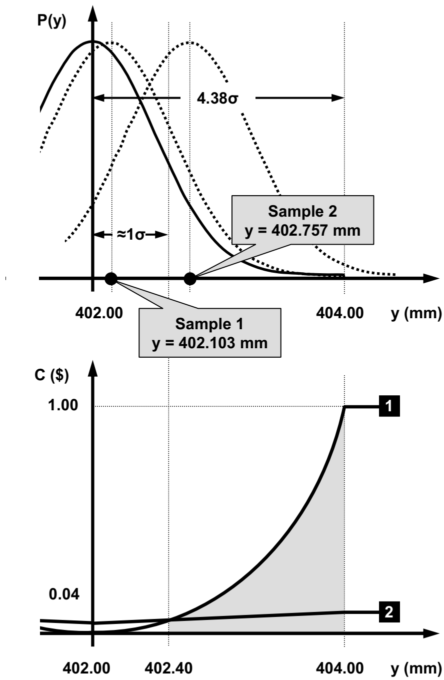

Figure 7.7: Relation between process deviation, quality costs and statistical distribution for example 1 (acceptable quality at sample 1, readjustment needed at sample 2)

Table 7.2: Input data for the quality cost trade-off of example 2

Parameter	Value	Parameter	Value
Run	1000 parts	Rework cost	150 $/part
Target	74.001 mm	Recovery cost	7500 $
USL	74.0182 mm		

Example 3

This example illustrates one fault case from the door assembly process described in Chapter 3. One previously described fault pattern (refer to Section 6.2.4.2) is a flushness fault at the lower corner of the door on the B-pillar side. The data needed for the cost model corresponding to this fault case is given in Table 7.3. The quality characteristic MP 10 is toleranced asymmetrically at +1.35/-0.15 mm. The expected fault frequency is estimated to be once a week according to process history and a run of 3500 doors is assumed (5 days * 700 doors). Thus, the process adjustment BEP for this fault case lies at a mean shift of +0.28 mm or -0.031 mm, i. e. a corrective action is justified once the deviation exceeds 20.5% of the allowed tolerance field.

The example shows the flexible application of the cost model to incorporate rework on a time basis and to accommodate asymmetrically toleranced features. The variable recovery cost component accounts for the additional tool calibration effort associated with this fault case.

Table 7.3: Input data for the quality cost trade-off of example 3

Parameter	Value	Parameter	Value
Run	3500 parts	Rework time	5 min
Target	0 mm	Cost per minute	0.85 €/min
USL	+1.35 mm	Recovery cost (fixed)	600 €
LSL	-0.15 mm	Recovery cost (variable)	100 €

Example 4

The data in this example relates to a fault case from the same door assembly line, where no rework is possible and the product has to be scrapped. Therefore, the cost of rework is replaced by that of scrap. Applying the cost trade-off to the process values given in Table 7.4, the allowed mean deviation before intervention is at 5% of the tolerance field. The value is relatively small and reflects the critical nature of this quality defect.

Example 4 suggests that care must be taken when applying the approach to high loss values, such as in the case of scrap. This is expected, as the underlying logic of the cost model implies a gradual increase in the incurred loss. Also, the ratio between the maximum loss due to poor quality and the maximum cost of process adjustment amounts to 400 in the example. This is approximately twenty times as much as the preceding examples, where better agreement with the actual real-world decisions could be achieved.

The approach offers another benefit if the process shows a gradually increasing deviation. After determining the BEP for the identified fault case, the available quality margin before intervention can be quantified. It is equivalent to the difference between the known BEP and the deviating process mean. Noteworthy is that the proposed cost model does not address the case of increased variation with unchanged process mean. Such a situation is conventionally detected by R-charts or indicated by an increase in outliers. In practice, however, such variation patterns are often accompanied by cyclic mean shifts that can be efficiently handled by the proposed system.

A final note is that errors in estimating the parameters of the QLF may not significantly affect the quality cost per product, as Taguchi reports [TAGUCHI et al. 1989]. Nevertheless, the careful choice of the parameter values is critical for successful application of the module and reduction of downstream problems.

Table 7.4: Input data for the quality cost trade-off of example 4

Parameter	Value	Parameter	Value
Run	10000 parts	Scrap cost	20 €/part
Target	0 mm	Recovery cost (fixed)	500 €
USL	0.38 mm	Recovery cost (variable)	80 €

7.4 Conclusion

The chapter presented a quantitative formulation of two decision criteria for fault recovery and process adjustment. The analysis procedure benefits from the synergy with the two previous modules: the combination with the early alarm capabilities of the fault recognition module and the possibility of case-specific cost estimation using the results of the fault identification module.

The conditional fault probability was modeled in a direct application of Bayes' Theorem. The results show how the adjustment decision can be delayed until its statistical plausibility has been established. The second issue is modeling the quality cost trade-off between the cost of process adjustment and the cost of poor quality. Mathematical expressions of both cost components were presented and validated through practical real-world examples. The quadratic QLF and the linear recovery costs offered very good approximations of the real process economics and proved as reliable indicators in the decision process.

Further research on these issues should cross-reference values of fault probability and quality costs from different and more diverse production scenarios. Such a study may lead to establishing a method for determining the required parameters. It also remains to be investigated if other forms of the QLF offer more benefits in quality cost modeling.

The detailed description of the components of the proposed diagnostic system is completed with the conclusion of this chapter. The next chapter describes the integration of the three system modules fault recognition, fault identification and decision into a unified platform.

8 Integration and reuse

8.1 Overview

The previous chapters addressed the components of a KBS for diagnosis and decision support in quality control activities. The components are contained in three modules, each having a specific functional area: recognition, identification and decision. This chapter describes the integration of these three modules into one homogeneous system as well as the integration of the diagnostic system with an existing measurement station. A prototype was realized for this purpose. An exemplary case summarizes the complete fault handling procedure. In addition, a reuse scenario is discussed to indicate the applicability of the proposed system to a diversity of production environments.

8.2 Experimental setup

The experimental setup shown in Figure 8.1 and Figure 8.2 was built to emulate a typical BIW measurement station and to test the developed software prototypes and their data interfaces. The communication medium was Ethernet and fiber-optic cables (FOC). A Perceptron® FlexiCam® sensor mounted on a KUKA® robot type KR-15/2 with a KRC control constitute the flexible measurement system. Part fixturing followed the 3-2-1 principle. The measurement reports are exported in XML-format[23] to the analysis PC through a local ftp-server[24] and read into the Matlab® environment.

8.3 Prototype of the integrated system

The developed diagnostic modules were cast into a software prototype programmed in Matlab®. Loose coupling [MEDSKER 1995] was implemented for data transfer between the modules. Loose coupling in its simplest form refers to communication through the export and import of separate data files. It decreases the complexity of the overall system and poses higher demands on the modularity of single system components. Figure 8.3 gives an overview of the information flow between the three modules.

[23] Extended mark-up language

[24] File transfer protocol

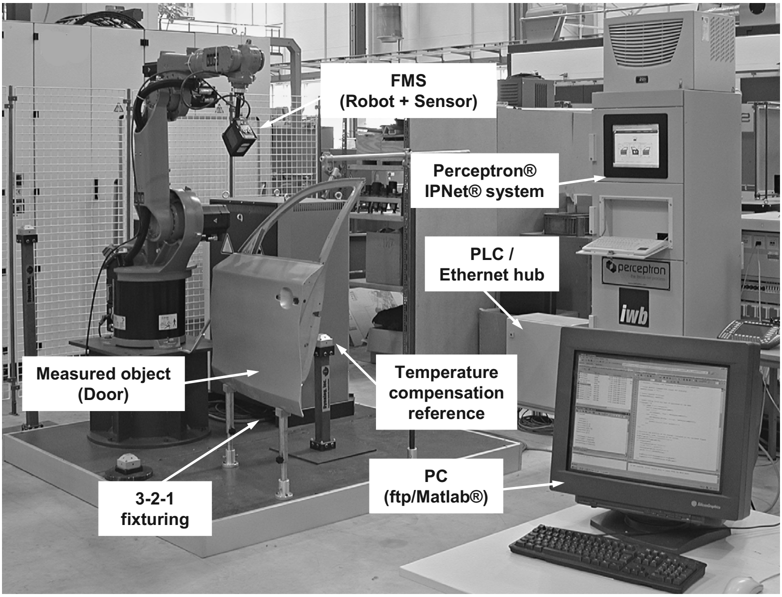

Figure 8.1: The realized experimental setup representing a typical BIW measurement station

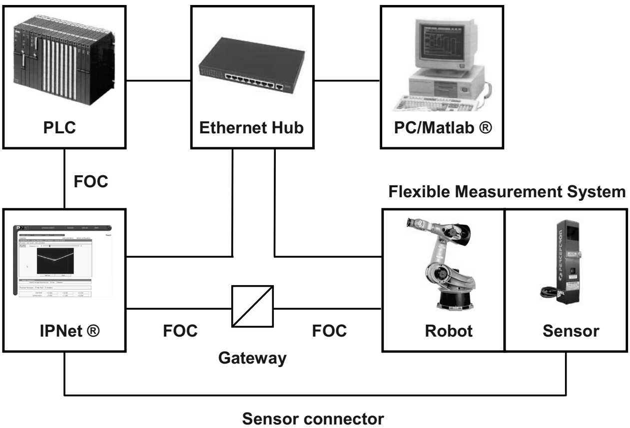

Figure 8.2: Schematic diagram of the realized experimental setup

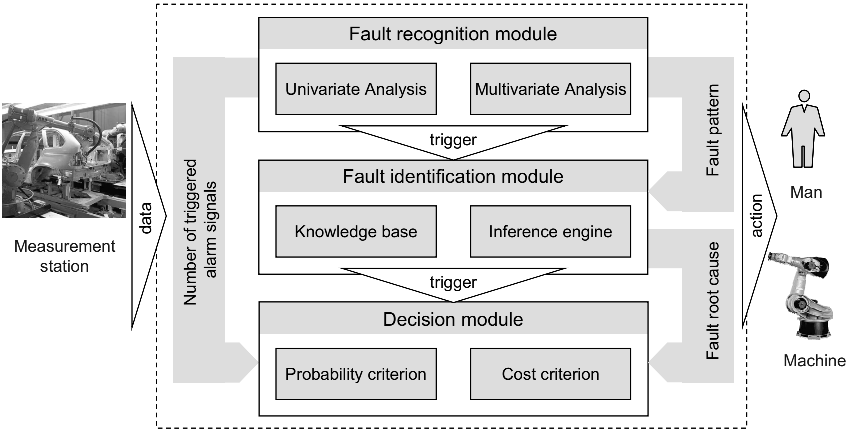

Figure 8.3: Information flow in the developed system

The prototype is acronymed ProRID (Process/Recognition, Identification and Decision). ProRID receives current geometry data from the measurement station after each measurement cycle. If the fault recognition module signals no alarm, the main graphical user interface (GUI) indicates a normal process (Figure 8.4). However, if the process is drifting and a fault pattern from the knowledge rule base could be associated with the process behavior, the result is similar to Figure 8.5. The alarm is based on the analysis results of the NN system described in Chapter 5, which acts as a trigger for the following stages.

In Figure 8.5, ProRID indicates process abnormalities, suggests the root cause and recommends whether to adjust the process immediately or later. If several fault cases share the same firing intensity, a message is generated accordingly. The panel titled *show analysis* leads to the details of the three involved analysis stages: recognition, identification and decision.

The ProRID recognition window (Figure 8.6) shows the current mean values of the monitored quality characteristics for an arbitrary number of measurement cycles. The panel *correlations* shows the results of the multivariate data analysis using the signs (o), (-) and (+) representing no correlation, negative correlation and positive correlation, respectively. The panel titled *legend* gives the location of the measurement points relative to the door geometry.

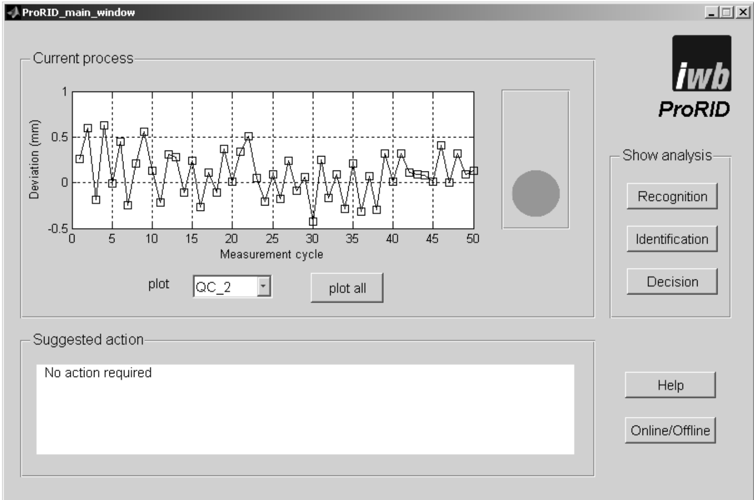

Figure 8.4: ProRID main window for normal process. The user can toggle between different quality characteristics (QC)

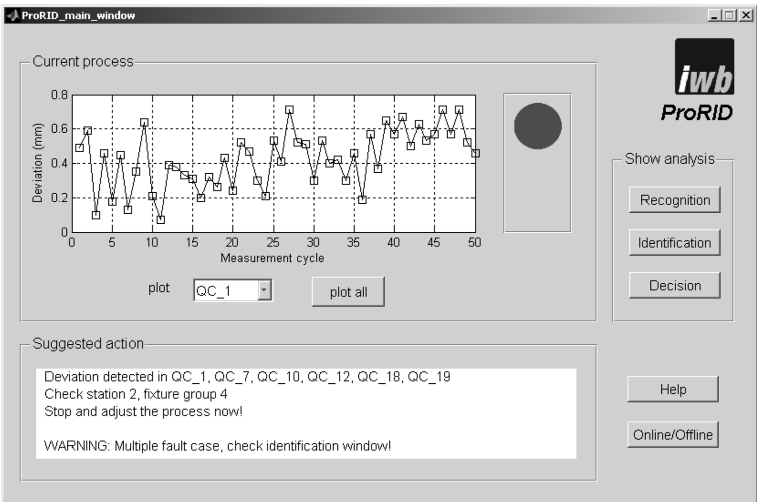

Figure 8.5: ProRID main window in the case of a quality defect

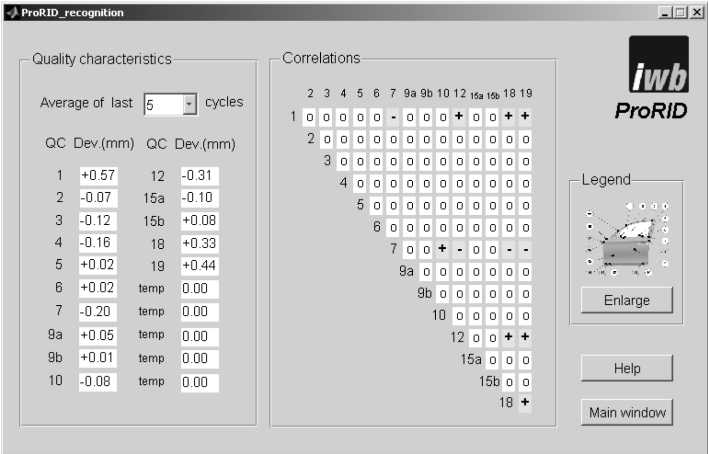

Figure 8.6: ProRID recognition window

The ProRID identification window (Figure 8.7) gives the inference results w.r.t. the fault knowledge base. The upper part of the window shows the triggered rules, their firing intensity and the associated fault risk priority. The lower part of the window is intended for the user in order to query the rule base. The figure shows rules 3 and 6 having identical firing intensities but different risk values. This explains why in the ProRID main window (Figure 8.5) the cause associated with rule 3 is accompanied by the warning message for other possible fault cases.

Figure 8.8 shows the ProRID decision window. The two upper panels give the results of the probability assessment and the cost trade-off described in Chapter 7. In addition to indicating the posterior fault probability according to Bayes' Theorem, the system informs the user how many alarm signals were issued in a preset interval of measurement cycles. At the point of detection, the maximum deviating quality characteristic, MP 18 was at 86 % of the tolerance field and is higher than the cost BEP designated to root cause 3, which was identified by the fault identification module. The bottom panel is intended for the user to query the set parameters corresponding to each fault case.

If alarm is signaled and the fault is unknown, the result given in the main window is based on the triggered alarm signals (univariate and multivariate analysis) and the fault probability component only.

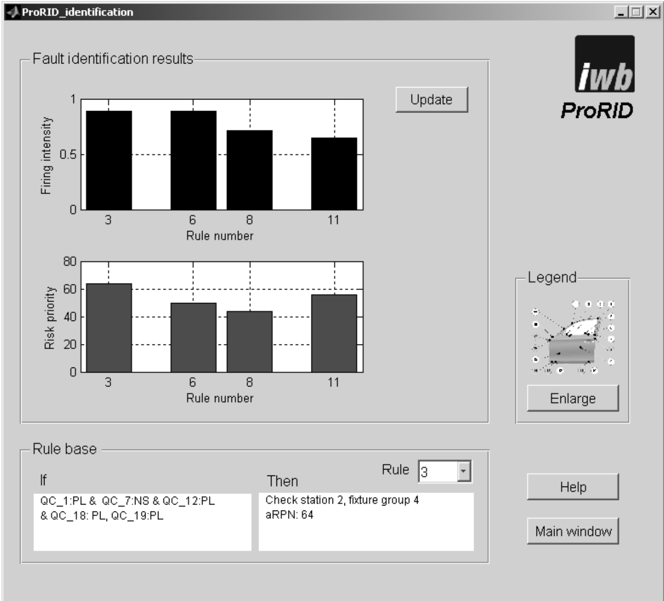

Figure 8.7: ProRID identification window

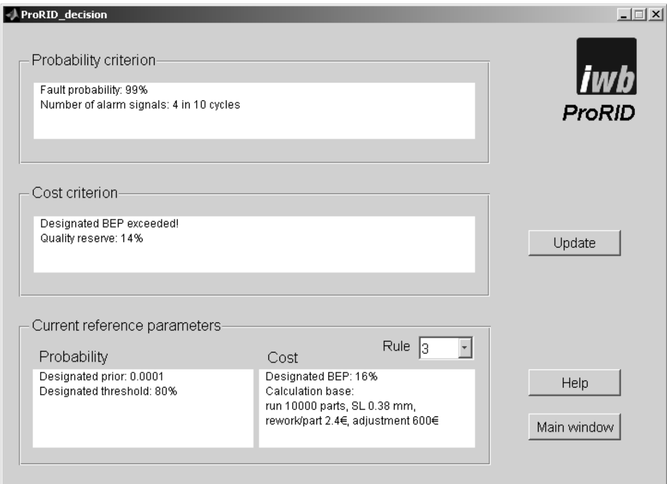

Figure 8.8: ProRID decision window

8.4 Illustrative reuse scenario

Before proceeding to the assessment of the developed system, its reuse is addressed in this section, i. e. its possible application to other manufacturing processes. A multi-stage machining process shown in Figure 8.9 is considered for illustration purposes. The exemplary process, adapted from HUANG et al. 2000, consists of four machining operations followed by an EOL quality inspection station. The monitored quality characteristics are listed in Table 8.1.

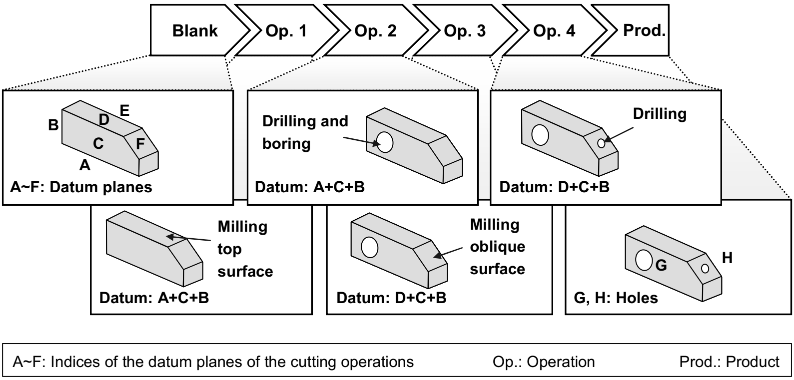

Figure 8.9: Exemplary multistage machining process [HUANG et al. 2000]

Table 8.1: Quality characteristics (QC) in the illustrated example according to HUANG et al. 2000

Label	Quality characteristic (Datum)	Label	Quality characteristic (Datum)
QC_1	Height D (A)	QC_6	Length of face D (B)
QC_2	Parallelism D (A)	QC_7	Diameter H
QC_3	Diameter G	QC_8	Y-pos. of hole H (C)
QC_4	X-pos. of hole G (B)	QC_9	Z-pos. of hole G (A)
QC_5	Z-pos. of hole G (A)	QC_10	Angularity of face F (A)

The first task after quality inspection is to investigate if unnatural patterns develop in successive measurement cycles. The application of the fault recognition module is straight forward in this case. Given that the quality characteristics follow a normal distribution, the same NN structure as designed in Chapter 5 can be directly implemented. Otherwise, the networks have to be retrained using process history or newly generated data. Applying similar monitoring conditions as described in Section 5.5.1.2, the recognition results described in Section 5.5.2 and Section 5.6 can be reproduced.

To apply the fault identification module, a new knowledge base is required. The product quality deviations in machining arise due to machining errors, fixturing errors and reorientation effects associated with datum change across operations. The datum refers to the reference plane(s) for the cutting operations. W.r.t. the described machining process, Table 8.2 presents sample diagnostic rules. In the sample, rules 1 and 2 are simple and involve direct identification of the root causes. Other rules (e. g. rule 5) capture the reorientation error in addition to the root cause. The conflict resolution strategy can be implemented for the machining case in the same manner as described for BIW.

Similar to the recognition module, the decision module is directly applicable in this reuse scenario since similar governing conditions to the assembly process prevail. Both, Bayes' Theorem and the developed cost model, can be adapted to the machining case provided that the required parameters can be determined.

Now that the integration of all three modules has been discussed, the next section discusses the expected impact of such a diagnostic system in a production environment, especially in the BIW case, from a technical as well as an economical viewpoint.

Table 8.2: Sample rules for the machining fault identification rule-base

<table>
<tr><th>Rule</th><th>If deviation is detected in</th><th>Then root cause is</th></tr>
<tr><td>1</td><td>QC_1 OR QC_2</td><td>Op.1, fixturing error/ adjust fixture</td></tr>
<tr><td>2</td><td>QC_4 OR QC_5</td><td>Op.2, fixturing error/ adjust fixture</td></tr>
<tr><td>3</td><td rowspan="2">QC_6</td><td>Op.3 fixturing error/ adjust fixture</td></tr>
<tr><td>4</td><td>Op.3, machining error/ check tool</td></tr>
<tr><td>5</td><td>QC_1 & (QC_5 OR QC_6)</td><td>Op.1 datum error/ adjust fixture</td></tr>
<tr><td>⋮</td><td>⋮</td><td>⋮</td></tr>
</table>

9 Impact on production performance – An assessment

9.1 Overview

This chapter presents a brief discussion of the technical and economic advantages, drawbacks and further potentials of the proposed diagnostic system. The technical assessment addresses common aspects of KBS implementation in production environments. The economic benefits are demonstrated in the terms of performance and profitability.

9.2 Technical assessment

The discussion in this section concentrates on four general assessment criteria of CAx applications in manufacturing that are often quoted in the literature and implemented in the industry: time, quality, reuse and synergy [EIGNER & STELZER 2001]. The criteria are addressed for the proposed system as compared to conventional inline measurement systems. In addition, user acceptance is briefly discussed as an important aspect relating to the organizational feasibility of the KBS approach [KINGSTON 2004]. An assessment of the specific technical details of the system modules was integrated in chapters 5, 6 and 7 and is not included in this section.

<u>Time</u>

MÜLLER 2006 estimates the time lost in maintenance, fault recovery and parameter adjustments in weld robots at 10% of the total production time. The figure indicates the potential for increasing the production efficiency if earlier fault recognition can be achieved. To the same end, the presence of a fault knowledge base, which provides the user with instructions for suitable countermeasures, is an additional time-saving factor.

On the contrary, the implementation of the system requires time for design and operation. In order to accurately quantify the required time, the knowledge base and parameter identification for cost and probability models must be integrated in a new vehicle launch project. However, the implementation time is expected to decrease with repeated implementation in compliance to common learning curves.

<u>Quality</u>

The focus of the thesis was to achieve stable quality levels through modeling the knowledge and the actions of the human expert. It was not attempted to achieve higher product quality in the sense of decreased tolerance fields or reactive mechanisms that affect the process. Thus, from a conservative viewpoint, the system does not contribute to higher product quality levels. Nevertheless, timely adjustment of the process leads to more consistent product characteristics. Also, considering the quality and the organization of the production process and not the product quality, savings as high as 2-5% of the sales volume are estimated [RUDOLF 2007]. These savings result from prevented faults, reduced rework and improved maintenance plans.

Reuse and expandability

The fault recognition module and the decision module are generally applicable to various production scenarios in their presented form. The main concern when addressing reuse lies rather in the components of the fault identification module: the knowledge base and the inference engine. Here, these three aspects have to be examined separately:

- Reuse for similar BIW assembly processes
- Reuse for other multistage manufacturing processes, such as machining or stamping operations
- Expandability of the system inputs and outputs

As discussed earlier, in BIW assembly of a family of vehicle models, the production lines have similar layouts. This implies that the diagnostic rules can be reimplemented but with an associated adjustment effort that varies inversely with the degree of similarity in process layout. Accordingly, when compared to a conventional BIW inline measurement station, the proposed system scores less on a reuse scale. The same argument is valid for reuse in the context of other manufacturing processes.

The third aspect refers to including process parameters in addition to the EOL measurement results in the fault analysis procedure. This represents an interesting development of the proposed system. As such, the system can be expanded to function as a supervisory process controller that reacts not only in normal operation (classical control) but also in the case of faults (fault-adaptive control). The implementation of such process adaptive techniques allows larger tolerance fields and more relaxed quality specifications of the upstream processes [MÜLLER 2006]. This, in turn, translates directly into reduced production costs.

In its extended form, the system inputs in BIW may incorporate monitoring of the spot welding process, robot position signals as well as optically captured fixture and part positions [EICHHORN 2005]. Similarly, in a machining scenario, input signals such as vibration and acoustic emission levels, electric drive current and spindle temperature can be included in the rule base conditions. The output signals of such a supervisory controller may allow automatic recovery if proper process interfaces are available. For the time being, however, the economic feasibility of automatic fault recovery in BIW is not given.

Synergy

Synergy refers to the indirect advantages of the presented approach that can be attained in different stages of the product lifecycle. Such additional benefits are expected mainly in the contexts of virtual ramp-up and management execution systems (MES).

Virtual ramp-up is widely practiced in the design phases of many manufacturing facilities [MIN et al. 2002, ZÄH et al. 2004]. It refers to the simulation of different process aspects such as PLC-architectures, controller codes and collision before or in parallel to hardware installations. The simulation of product quality and process capability is also proposed as part of a virtual ramp-up [LANZA 2005, LANZA et al. 2006]. Integrating the knowledge acquisition phase as described in Section 6.2 into virtual ramp-up procedures promises early and consistent knowledge management w.r.t. modeled fault patterns as well as to process heuristics. Casting this knowledge into a software tool guarantees proper storage and availability of quality planning results to the operation personnel. Early access to fault knowledge can be highly beneficial, especially in the light of the fact that 70 % of the geometry faults in the launch phase of new vehicle models is attributed to fixture failure [HU 1997].

The functions of the developed software prototype (Section 8.3) can be integrated in standard MES or SCADA architectures easily. In this way, no additional infrastructure is needed and the communication between different fault analysis stations, process engineers and management is supported.

Acceptance

The acceptance and the support of all stakeholders are crucial for a successful implementation of a KBS. KBS stakeholders include management, developers, experts and users. The first two groups have obvious interest in the success of the KBS. The human expert must be dealt with tactfully and must be allowed to have the upper hand at all times [KINGSTON 2004].

KBS application is generally subject to negative stereotypes, mainly among the users or the operation personnel. They are assigned the task of working with a new system, which is considered inconvenient, and are often skeptical of the outcome. The social impact of implementing KBS is not limited to its launch only. For example, repeated user override may lead to loss of confidence in the system. Also, other issues have to be clear as early as possible, such as who is responsible for the maintenance of the KBS and how it would not lead to long-term deskilling of the workers [DYM & LEVITT 1991].

Figure 9.1 summarizes the technical assessment.

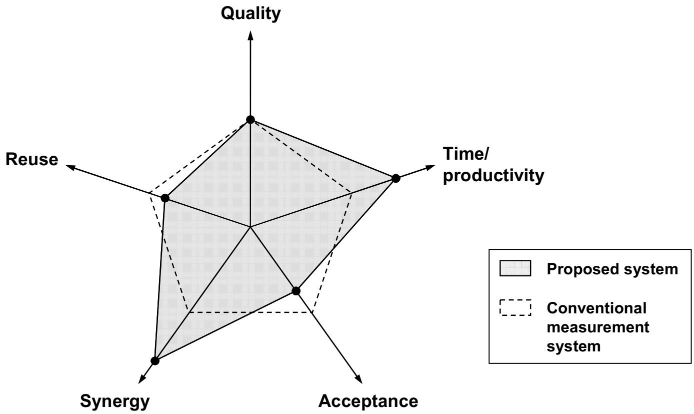

Figure 9.1: Qualitative comparison between the proposed system and a conventional inline measurement system in BIW assembly

9.3 Economic assessment

It is generally difficult to isolate the share of quality-related costs of an activity since cost targets are usually affected by the interaction of several activities and decisions [MASING 1988]. A look at the aspect of synergy described in the previous section gives an idea how intricate these activities may be. Quality costs cross department lines by involving all actions of the company. Consequently, it is difficult to estimate the quality costs[25] of a product unit [GEIGER 1994]. GEIGER 1994 attributes some negative as well as positive consequences to the special nature of quality costs. One negative consequence is that quality costs cannot be represented on a balance sheet from an accounting point of view. Another negative effect is seen in some company performance reports where the term *quality* is avoided and replaced by more general concepts such as total quality management. A positive consequence, however, is that the rough estimation of quality costs is satisfactory in industrial practices. Hence, the following discussion of the economic value of the proposed system is mostly qualitative in nature.

[25] The quality costs in this context extend to a company-wide cost viewpoint as compared to the local PAF model used in Chapter 7.

PAF cost analysis

The PAF quality cost model (Section 7.3.2.1) is a generally acknowledged tool for estimating quality costs. For most companies 5% of the quality costs are spent on prevention. 95% of the quality costs are expended on failure and appraisal that add no value to the product [JURAN & GYRNA 1988, HERING et al. 1994, GUH & O'BRIEN 1999]. Increasing expenditure on prevention can reduce the overall quality costs by 30-50% (Figure 9.2) [TANGRAM TECHNOLOGY 2005]. Depending on the application field, this may be equivalent to a profit increase of approximately 50%.

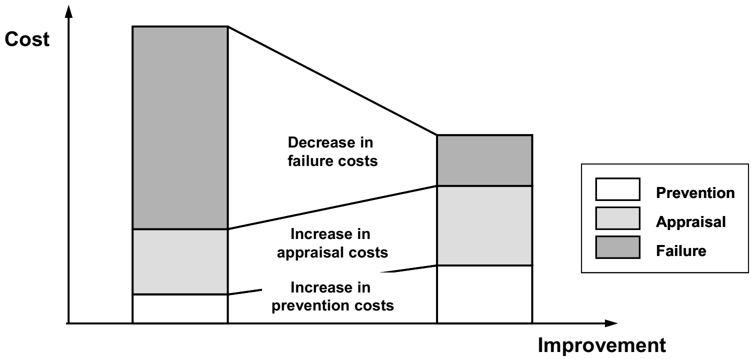

Figure 9.2: Cost reduction through reallocation of resources (qualitative representation)

Cost-benefit analysis of CAQ applications

Figure 9.3 illustrates a simplified cost-benefit balance for CAQ applications. The required initial hardware costs of the KBS are relatively low since the system consists mainly of software modules that can be annexed to inline measurement systems or, if available, to MES. The initial software costs, especially for the development of the rule base, are comparably high. The main cost contributor in this regard is the manpower and the required validation of the rule base. Staff training is necessary to overcome the aforementioned social and technical barriers of KBS application. The main work load associated with developing and maintaining the rule base lies on the quality planners assisted by the operational quality staff.

The following figures serve as monetary indicators of the expected benefit of a knowledge-based diagnostic system in the BIW manufacturing facility described in Chapter 3. Eliminating one manual rework station means a saving of approximately 230,000 € of the initial investment at current market prices. Eliminating one minute of the average rework time per produced vehicle corresponds to annual savings of approximately 180,000 €. The savings may not seem significant compared to the total production budget, but adding other benefits such as the opportunity for increased productivity and better planning of maintenance, repair and overhaul activities, the proposed system represents a strategically important and justifiable investment.

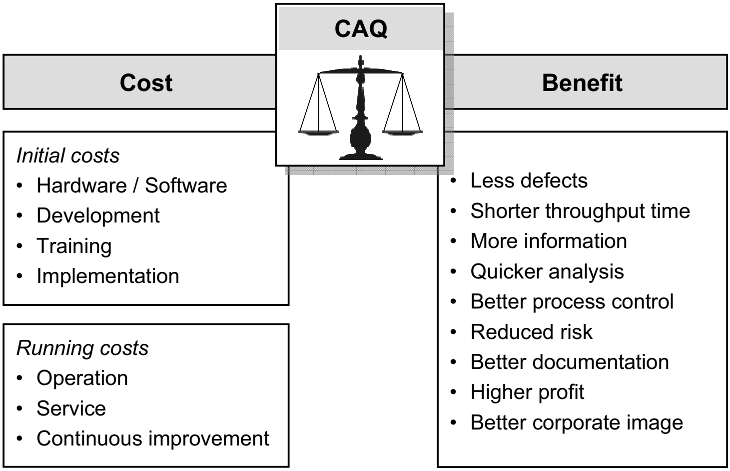

Figure 9.3: Simplified cost-benefit analysis of CAQ applications [HERING et al. 1994]

Impact on business performance

Over the years, rapid technical advances and technology mergers have resulted in continuous sophistication and improvements in the price-performance ratio of IT applications [VENKATRAMAN & ZAHEER 1990]. The improvement can be cast in terms of the relative prices of capital and labor, i. e. the ratio of the cost of a technology to the cost of labor. Over a period of thirty years, BENJAMIN et al. 1984 found that for products such as passenger vehicles and production machinery, the ratio improved at approximately two times per decade, i. e. a decrease in the price-performance of capital versus labor. In contrast, over the same period, the performance of the IT industry has shown an improvement of as much as twenty-five times. These developments make it possible to utilize IT-based applications at a fraction of the costs that would have been a few years before.

The following quote from a Frost & Sullivan[26] strategic report [FROST & SULLIVAN 2005] indicates the sustainability of the trend in the IT industry. The report focused on a number of European manufacturers and covered a variety of industrial sectors including the automotive industry.

"Increasing cost of raw materials along with competition from low-cost producers ... has driven plant modernization and forced European manufacturers to cut costs. ... The net effect should see continued investment in automation and control solutions ... as these systems are vital in achieving production synergies and eliminating costs in the manufacturing process."

[26] Frost & Sullivan Ltd., San Antonio, TX, USA <www.frost.com>

10 Summary and future research

Quality is a key element to long run success of engineering businesses [ONO & NEGORO 1992, KONDO 1995]. In many industries, 100% monitoring has become an established quality inspection strategy that saves valuable time when reacting to faults. It reduces risks and guarantees customer satisfaction by eliminating all defects. However, monitoring techniques are not capable of diagnosing faults or suggesting recovery actions. The latter aspect depends heavily on human experience in analyzing faults and conducting proper process adjustments in an economical way that contributes to improved profitability.

The outset of the thesis identified some disadvantages in current quality control practices in manufacturing facilities. A field study in the automotive industry showed that the analysis of quality defects and the elimination of their root causes is an underestimated task that exploits considerable resources. In many industrial applications, monitoring capabilities are restricted to the use of alarm thresholds. Also, the process of fault analysis is highly subjective as it depends on human expert judgment. In addition to the complex nature of quality problems in BIW production, organizational aspects such as staff rotations and sparing fault documentation add to the difficulty of the task. The problem, thus, boils down to the way process knowledge is implemented in production operations, especially when related to quality and fault troubleshooting issues.

Based on the results of a field study and a literature survey, the objective of the thesis was to investigate the need, the architecture and the development of a KBS for fault diagnosis and decision support in online quality control of manufacturing processes with the example of BIW assembly. The developed system targets the reduction of fault analysis time while increasing the certainty of the fault analysis. The fault knowledge base thus stores human expertise in quantifiable form and offers an approach to automated fault documentation. For this purpose, the proposed approach breaks down the diagnosis problem into three modules each performing two major tasks.

The fault recognition module examines the monitored quality characteristics for univariate and multivariate unnatural patterns such as mean shifts and trends or correlations. The NN-based module reached an overall univariate recognition certainty of 93.2 %. Error type I and type II were 1 % and 5.2 %, respectively. The multivariate analysis relies on the results of the univariate stage and uses several consecutive bivariate comparison steps to determine correlations in the quality characteristics. The introduced concept outperformed the conventional linear correlation coefficient and achieved an overall certainty of 94.3%. The concept represents a robust alternative that can be extended without further changes to include further patterns of linearly and nonlinearly correlating characteristics.

The fault recognition module addresses the localization of fault root causes upon the recognition of quality defects. The module contains a fault knowledge base, where the knowledge structure is adapted from a FMEA and is stored in rule form. For the rule base design, general-purpose and specific-purpose knowledge acquisition tools were necessary. The premise of the formulated rules described the measurement vector as obtained from the inspection station for a certain quality nonconformance pattern. The consequent part described possible root causes and provided a quantification of the associated risk and probability. A fuzzy inference engine was designed to infer the final decision on the root cause. Moreover, a conflict resolution strategy was developed that implements a risk criterion to enhance fault diagnosability. It could be shown that the rule base and the fuzzy inference engine are capable of capturing the expert knowledge in BIW in an intuitive and practical way. The rule base can be reimplemented for similar assembly lines and extended to include process parameters in addition to the quality characteristics in the rule premise.

The third module, the decision module, relates the decision of adjusting the process to the fault conditional probability and the associated cost of poor quality. The conditional fault probability is calculated through Bayes' Theorem making use of the consecutive alarm signals issued by the fault recognition module. The second criterion assesses the process economics in the case of a fault by modeling a cost trade-off between the incurred quality loss as defined by Taguchi and the fault recovery costs. Practical examples illustrated the validity of the theoretical assumptions for real-world application.

The three modules were integrated in a software prototype (ProRID). An experimental setup was realized for testing the developed software and its interface to the measurement system. Additionally, the reuse aspect of the developed system was discussed for an arbitrary machining process.

Compared to conventional inline measurement systems, the proposed KBS promises higher productivity and efficiency through earlier alarms and reliable decision support in the case of quality defects. The effect is targeted through increasing investments in the fault prevention area while expecting a larger decrease in failure costs, such as costs due to delayed reaction and analysis time. The synergy between the fault KBS and MES or SCADA systems offers advantages w.r.t. the integration with existing IT infrastructure and the initial hardware costs.

Two major research directions are suggested for the future development of the proposed diagnostic KBS. The first direction is the extension of the system capabilities to match online supervisory control systems. As such, process control even in the presence of minor faults would be possible. In the same line, research in the area of sensor networks complementary to EOL measurement is of great value to enhance the observability and the controllability of the production process. Related research results are already available on related topics such as sensor location optimization [KHAN & CEGLAREK 1998, LIU & DING 2005] and the design of sensor networks [DING et al. 2003, ZORRIASSATINE et al. 2003].

The second direction is the cross-functional information and knowledge sharing along the complete production cycle. The concept is represented schematically in Figure 10.1 for the automotive industry. Through forward and backward information flow between distributed quality gates, the product quality characteristics can be controlled more efficiently and economically. This in turn would reduce production costs, since better control of the process will allow for the implementation of larger geometrical tolerances.

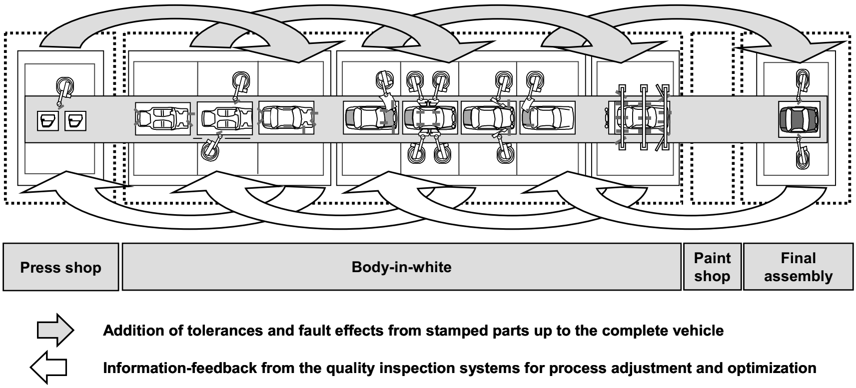

Figure 10.1: Forward and backward information flow from the geometrical measurement stations in the production cycle of a vehicle[27]

[27] Courtesy of Perceptron GmbH

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12 Appendix

12.1 Companies named in the thesis

BMW

Bayerische Motoren Werke Aktiengesellschaft

Munich, Germany

www.bmwgroup.com

www.bmw.de

www.bmw-werk-regensburg.de

Frost and Sullivan

Frost and Sullivan Ltd.

San Antonio, TX, USA

www.frost.com

KUKA

KUKA Roboter GmbH

Augsburg, Germany

www.kuka.com

Perceptron

Perceptron, Inc.

Plymouth, MI, USA

Perceptron GmbH

Munich, Germany

www.perceptron.com

Straatum

The Straatum Group

Dublin, Ireland

www.straatum.com

12.2 Some fundamentals of neural networks[28]

Definition

The development of artificial neural networks, commonly referred to as neural networks (NN) has been motivated by the acknowledgment that the human brain computes in an entirely different way from the conventional digital computer. The brain is a highly complex, nonlinear, and parallel computer and NN are mathematical models of theorized brain activity. A commonly cited definition of NN states that:

"A neural network is a massively parallel distributed processor made up of simple interconnected processing units, known as neurons, which has a natural propensity for storing experiential knowledge and making it available for use. It resembles the brain in two respects:

- *Knowledge is acquired by the network from its environment through a learning process.*
- *Interneuron connection strengths, known as synaptic weights, are used to store the acquired knowledge."*

In this regard a learning algorithm performs the learning process and modifies the synaptic weights of the NN to attain a design objective. Another less traditional practice in the design of NN is the modification of the network topology, which is inspired by the fact that brain cells may die and new synaptic connections can grow.

Benefits

NN derive their computational power from their parallel structures and their ability to learn and generalize. Generalization refers to the NN producing reasonable outputs for inputs not encountered during training (learning). NN are capable of solving large-scale problems that are otherwise intractable. The application of NN offers a number of benefits, the foremost of which are nonlinearity, input-output mapping, and adaptivity. A NN is nonlinear if it is made up of an interconnection of nonlinear neurons. Nonlinearity is imperative when modeling phenomena or systems that are inherently nonlinear, such as in speech recognition applications. Input-output mapping refers to the viewpoint of a NN as a nonparametric or a model-free estimator. The NN uses training samples to modify its synaptic weights – free parameters – in order to minimize the difference between the desired output corresponding to a certain input and the actual output delivered by the network for the same input. The third beneficial aspect of NN is adaptivity. NN are capable of adapting their synaptic weights (retraining) to

[28] This section is based largely on HAYKIN 1999.

changes in the surrounding environment. The NN is superior when dealing with non-stationary operating conditions in signal processing and control applications.

The neuron

The main structural constituent of the NN is a neuron. The block diagram in Figure 12.1 shows the model of a neuron where three basic elements can be identified:

- The synapses or the connecting links, which are characterized by weights or connection strengths.
- The adder or the summing junction, which combines all inputs to the neuron in a linear or a nonlinear manner.
- The activation function, which limits the amplitude of the neuron output. The output of a neuron typically assumes a value in the interval [-1,1].

An optional element in the neuron model is the *bias*, which may be applied to increase or lower the net input of the activation function. The neuron k is described mathematically by the following two equations:

$$v_k = \sum_{j=0}^{m} w_{ki} x_j \tag{12.1}$$

$$y_k = f(v_k) \tag{12.2}$$

where:

$f(\cdot)$:	activation function
v_k:	induced local field or activation potential of neuron k
w_{k0}:	bias of neuron k
w_{ki}:	connection weight from neuron i to neuron k
x_0:	unit input to account for the bias
x_i:	input signal from neuron i to neuron k
y_k:	output signal of neuron k

The activation function, denoted by $f(\cdot)$, defines the output of the neuron in terms of its induced local field v. The basic types of activation functions include the threshold function, the linear function and the sigmoid function. The threshold function, known in engineering applications as the Heaviside function describes the all-or-none property of the model. The piecewise linear function is an approximation to a nonlinear amplifier. The sigmoid function is the most widely used in NN applications and is described as an s-shaped, strictly increasing function that balances between linear and nonlinear behavior. Table 12.1 gives the mathematical expressions corresponding to these three types of activation functions.

Table 12.1: Examples of the activation function

Threshold function	Piecewise linear function	Logistic sigmoid function
$f(v)=\begin{cases}1, & \text{if} \quad v \geq 0 \\ 0, & \text{if} \quad v < 0\end{cases}$	$f(v)=\begin{cases}1, & \text{if} \quad v \geq +\frac{1}{2} \\ v, & \text{if} \quad +\frac{1}{2} > v > -\frac{1}{2} \\ 0, & \text{if} \quad v \leq -\frac{1}{2}\end{cases}$	$f(v)=\dfrac{1}{1+\exp(-av)}$ (a : slope parameter)

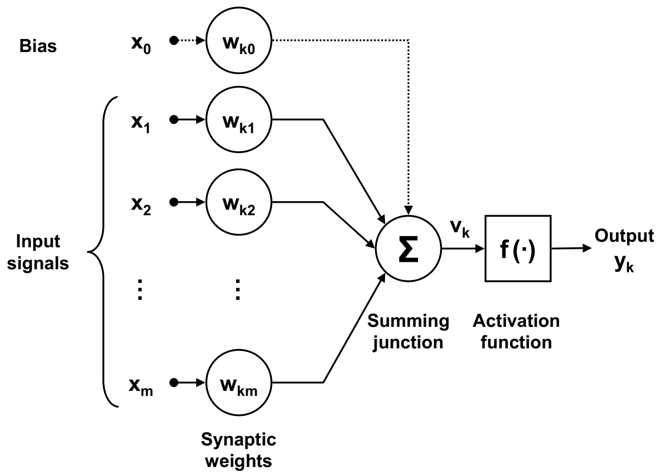

Figure 12.1: Model of a neuron

Topology

In general, a *layered* NN may have one of three fundamentally different topologies:

Single-layer feedforward networks

The simplest form of layered NN is the single-layer NN.

Multilayer feedforward networks

A layer that receives signals from the environment is called an input layer and a layer that emits signals to the environment is an output layer. Any layer in between is called a hidden layer. By adding the hidden neurons, the network is capable of capturing higher order models and statistics. This feature is especially critical if the size of the input vector is large.

Recurrent networks

In contrast to feedforward network structures, a recurrent NN contains at least one feedback loop. In this topology, a neuron can feed back its output signal to neurons of preceding layers, to neurons of the same layer (intra-layer), or to itself (self-feedback). Recurrent NN may consist of one or more layers.

In all three topologies the NN may be fully or partially connected. The latter refers to the situation when some synapses are excluded in the network design. This is equivalent to assigning a synaptic weight of zero to a connection. Figure 12.2 depicts a three-layer fully connected feedforward NN.

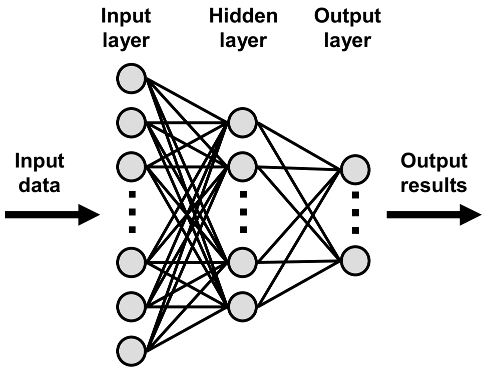

Figure 12.2: Topology of a multilayer feedforward NN with three layers

Learning

Learning in the context of NN may be defined as:

"Learning is a process by which the free parameters of a neural network are adapted through a process of simulation by the environment in which the network is embedded. The type of learning is determined by the manner in which the parameter changes take place."

The set of well-defined rules for the solution of the learning problem is called a *learning algorithm* or *learning rule*. The topology of a NN is intimately linked with the learning algorithm used to train the network. However, there is no unique training algorithm for a certain NN. Learning algorithms differ from each other in the way the synaptic weights are adjusted and the way the NN relates to its environment (*learning paradigm*).

The most widely used learning algorithms represent either direct applications or derivatives of five basic learning algorithms: error-correction learning, memory-based learning, Hebbian learning, competitive learning, and Boltzmann learning. Error-correction learning is an optimum filtering technique. Memory-based learning memorizes the training data explicitly. Hebbian learning and competitive learning implement concepts rooted in neurobiology, where, for example, more active synapses are rewarded with higher credits or weights. Boltzmann learning implements ideas borrowed from statistical mechanics. To provide a brief insight into NN learning mechanisms, the error-correction learning is described in the next section.

Two fundamental learning paradigms prevail in NN applications: learning with a teacher and learning without a teacher. The concept of learning with a teacher, also referred to as supervised learning, is illustrated in Figure 12.3. Here, the teacher provides the learning system, which is a NN in this case, with data pairs of input vectors and their corresponding desired outputs. The learning system adapts its parameters in order to minimize the deviation between the desired and the actual response. On the contrary, learning without a teacher, there is no teacher to oversee the learning process. The two subdivisions of this paradigm are reinforcement learning and unsupervised learning (Figure 12.4). In reinforcement learning, a critic evaluates the performance of the learning system in relation to the environment. The evaluation results are implemented to adjust the learning system through predefined mechanisms, such as cost functions. The unsupervised or self-organized learning includes neither a teacher nor a critic. The network parameters are rather optimized with respect to a task independent measure. Regardless of the presence of a teacher, the learning process can be conducted before the actual implementation of the NN (offline) or during operation (online).

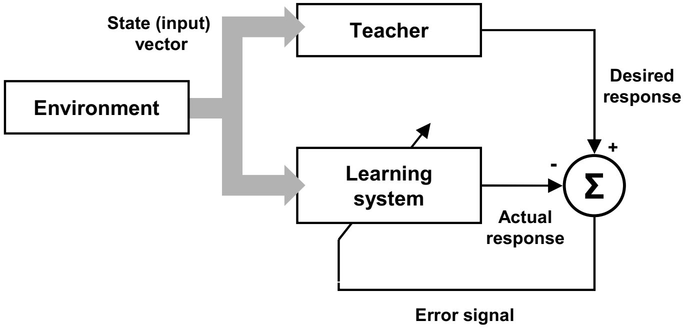

Figure 12.3: Learning with a teacher (supervised learning)

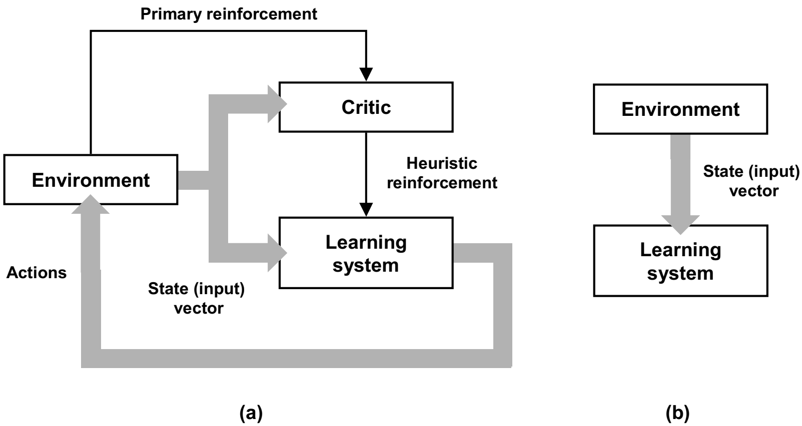

Figure 12.4: Two paradigms for learning without a teacher: (a) reinforcement learning and (b) unsupervised learning

Error-correction learning

Consider a feedforward NN with a single neuron in its output layer, denoted k. The error e is defined as the difference between the desired output d and the actual output y and is given by Equation 12.3 as follows:

$$e_k(n) = d_k(n) - y_k(n) \qquad (12.3)$$

where n denotes discrete time or the time step of the iterative process of adjusting the synaptic weights of neuron k. The error signal actuates a control mechanism, which adjusts the synaptic weights of the neuron in order to minimize a given cost function in a step-by-step manner. The cost function E is defined in terms of the error as:

$$E_k(n) = \frac{1}{2} e_k^2(n) \tag{12.4}$$

Thus, E represents the instantaneous value of the error energy. The adjustment is iterated until the weights have reached a steady state or met a predefined threshold.

Let w_{kj} denote the synaptic weight of the neuron k excited by x_j, which represents an element of the input vector to the neuron x(n). Thus, the adjustment Δw_{kj} applied to the weight w_{kj} at time step n is:

$$\Delta w_{kj}(n) = \eta e_k(n) x_j(n) \tag{12.5}$$

where η is a positive constant that determines the *learning rate*. Equation 12.5 describes the learning rule known as the delta rule, which may be stated as:

"The adjustment made to a synaptic weight of a neuron is proportional to the product of the error signal and the input signal of the synapse in question."

The updated weight of the synapse is determined by:

$$w_{kj}(n+1) = w_{kj}(n) + \Delta w_{kj}(n) \tag{12.6}$$

As such, the error-correction learning is an example of a closed-loop feedback system working locally in the vicinity of a neuron. The stability and the performance of the algorithm are governed by its parameters, especially the learning rate. The learning-rate parameter η must be carefully chosen to ensure the convergence and the accuracy of the algorithm

Backpropagation training for multilayer feedforward neural networks (MFNN)

MFNN are an important class of NN that finds vast practical application. In these networks, the input signal propagates through the network in a forward direction, on a layer-by-layer basis. MFNN have been applied successfully to solve complex real-life problems in many application domains. In particular, the supervised training of MFNN with the highly popular algorithm known as the *error backpropagation algorithm* is reported to be a superb technique.

The error backpropagation algorithm or simply backpropagation (BP) is based on the error-correction learning. It basically consists of two passes through the layers of the NN: a forward pass and a backward pass. In the forward pass, an input vector is applied to the input nodes of the network, and its effect propagates through the network, layer by layer. A set of outputs is produced as the actual response of the network. During the forward pass the synaptic weights of the network are all fixed. Next, an error signal, defined as the difference between the actual response of the network and a desired response, is propagated backward through the network, against the direction of synaptic connections. The synaptic weights are adjusted so as to make the actual network response closer to the desired response of the network. This scheme of weight adjustment repeats many times until the weights no longer change, a condition referred to as convergence of the learning algorithm.

There are two ways (or modes) to adjust the weights using backpropagation. One approach, the pattern mode, adjusts the weights based on the error signal of one input output pair in the training data. Thus, these adjustments are made immediately after each training datum is fed into the neural network. The other approach, referred to as batch or epoch mode of backpropagation learning, adjusts weights based on the error signal of the entire training set. Therefore, weights are adjusted once only after all the training data have been processed by the neural network. The gradient descent method is used to minimize the error between the actual and desired network outputs of the entire training set. The next section provides a mathematical description of the pattern BP algorithm applied to an arbitrary neuron in the output layer.

Backpropagation algorithm

Pattern-by-pattern backpropagation learning applies the gradient descent method to a cost function representing the error energy. The total instantaneous error energy E(n) over the set C containing all neurons of the output layer of a MFNN is given by

$$E(n) = \frac{1}{2}\sum_{j \in C} e_j^2(n) \tag{12.7}$$

Consider a neuron j in the output layer being fed by m input signals from the layer to its left. The induced local field is given by:

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n) y_i(n) \tag{12.8}$$

Hence, the output of neuron j is:

$$y_j(n) = f_j(v_j(n)) \tag{12.9}$$

The backpropagation algorithm applies corrections to the synaptic weights $\Delta w_{ji}(n)$ proportional to the partial derivative $\frac{\partial E(n)}{\partial w_{ji}(n)}$, which is a sensitivity factor determining the direction of search in weight space for the synaptic weights. Using the chain rule, the derivative can be written as follows:

$$\frac{\partial E(n)}{\partial w_{ji}(n)} = \frac{\partial E(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \frac{\partial v_j(n)}{\partial w_{ji}(n)} \tag{12.10}$$

By differentiating Equation 12.7 with respect to $e_j(n)$:

$$\frac{\partial E(n)}{\partial e_j(n)} = e_j(n) \tag{12.11}$$

Similarly, differentiating Equation 12.3 with respect to $e_j(n)$:

$$\frac{\partial e_j(n)}{\partial y_j(n)} = -1 \tag{12.12}$$

Next, differentiating Equation 12.9 with respect to $v_j(n)$:

$$\frac{\partial y_j(n)}{\partial v_j(n)} = f'(v_j(n)) \tag{12.13}$$

Finally, differentiating Equation 12.8 with respect to $w_{ji}(n)$:

$$\frac{\partial v_j(n)}{\partial w_{ji}(n)} = y_i(n) \tag{12.14}$$

Consider the delta rule:

$$\Delta w_{ji}(n) = -\eta \frac{\partial E(n)}{\partial w_{ji}(n)} \tag{12.15}$$

where η is the learning-rate parameter and minus sign accounts for gradient descent. Substituting Equations 12.10 through 12.14 into the delta rule:

$$\Delta w_{ji}(n) = \eta \delta_j(n) y_i(n) \tag{12.16}$$

where $\delta_j(n)$ is the local gradient defined as:

$$\begin{aligned} \delta_j(n) &= -\frac{\partial E(n)}{\partial v_j(n)} \\ &= -\frac{\partial E(n)}{\partial e_j(n)} \frac{\partial e_j(n)}{\partial y_j(n)} \frac{\partial y_j(n)}{\partial v_j(n)} \\ &= e_j(n) f'(v_j(n)) \end{aligned} \tag{12.17}$$

Once the local gradient is calculated for the output neuron j, the required change in the synaptic weights can be determined. The calculation of synaptic weight changes in hidden neurons follows the same concept. In this case the error signal of the hidden neuron has to be determined recursively in terms of the error signals of the neurons it abuts in the neighboring layer nearer to the output layer.

12.3 Some fundamentals of fuzzy math

Fuzzy sets

Fuzzy set theory generalizes the classical set theory to allow partial membership. A set in classical set theory always has a sharp boundary; an object either completely belongs to the set or does not belong to the set at all. A fuzzy set is a set with a smooth boundary. The degree of membership in a set is expressed by a number between 0 and 1; 0 means entirely not in the set, 1 means entirely in the set, and a number in between means partially in the set. A fuzzy set is thus defined by a function that maps objects in a domain of concern to their membership value in the set. Such a function is called a membership function denoted μ.

A fuzzy set is often associated with a linguistically meaningful term. The use of a linguistic variable offers two important benefits. Firstly, it is easier for a human expert to express his knowledge in linguistic terms. Secondly, knowledge expressed in linguistic terms is easily comprehensible and transferable, thus resulting in significant savings in the design and maintenance costs of a fuzzy logic system.

Membership functions

A membership function provides gradual transition from regions completely outside a set to regions completely in the set. The membership function can have an arbitrary shape determined by setting a number of parameters depending upon the chosen shape. Among the most common membership functions used in practice are triangular and trapezoid. Other types of membership functions include bell curves, Gaussian, and sigmoidal functions. The triangular membership function (Figure 12.5) can be described mathematically by the following equation.

$$\text{triangle}(x : a, b, c) = \begin{cases} 0 & x < a \\ \dfrac{x-a}{b-a} & a \le x \le b \\ \dfrac{c-x}{c-b} & b \le x \le c \\ 0 & x > c \end{cases} \tag{12.18}$$

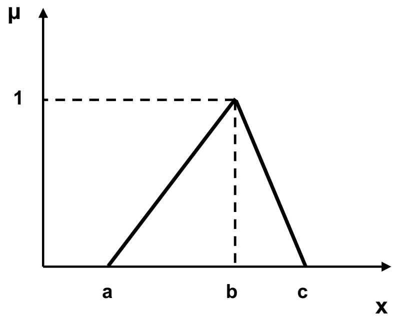

Figure 12.5: Triangular membership function

Basic operations on fuzzy sets

The fundamental operations in classical sets are union, intersection, and complement. The union of two sets A and B (denoted $A \cup B$) is the collection of those objects that belong to either A and B. The intersection of A and B (denoted $A \cap B$) is the collection of those objects that belong to both A and B. The complement of a set A (denoted $\overline{A}$) is the collection of objects not belonging to A.

Since membership in fuzzy sets is a matter of degree, set operations should be generalized accordingly. Union, intersection, and complement operations in fuzzy set theory are similar to conjunction, disjunction, and negation in logic. Common fuzzy disjunction operators include the maximum operator and algebraic sum.

$$\mu_{A \cup B}(x) = \max\{\mu_A(x), \mu_B(x)\} \tag{12.19}$$

$$\mu_{A \cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) \times \mu_B(x) \tag{12.20}$$

Common fuzzy conjunction operators include the minimum operator and the algebraic product.

$$\mu_{A \cap B}(x) = \min\{\mu_A(x), \mu_B(x)\} \tag{12.21}$$

$$\mu_{A \cap B}(x) = \mu_A(x) \times \mu_B(x) \tag{12.22}$$

The complement of a fuzzy set reflects negation. The compliment of the fuzzy set A can be defined by the difference between one and the membership degree in A:

$$\mu_{\overline{A}}(x) = 1 - \mu_A(x) \tag{12.23}$$

It is important to notice that the choice of a fuzzy conjunction operator determines the choice of the fuzzy disjunction operator, and vice versa. This is due to the principle of duality between the two operators. A fuzzy conjunction operator, denoted t(x,y) (triangular norm) and a fuzzy disjunction operator, denoted s(x,y) (triangular co-norm), form a dual pair if they satisfy the following condition:

$$1 - t(x, y) = s(1 - x, 1 - y) \tag{12.24}$$

Thus, the duality condition ensures that De Morgan's laws

$$\overline{A \cap B} = \overline{A} \cup \overline{B} \tag{12.25}$$

$$\overline{A \cup B} = \overline{A} \cap \overline{B} \tag{12.26}$$

hold in the fuzzy set theory. Minimum and maximum operators or algebraic product and algebraic sum operators form a typical pair of t-norms and s-norms.

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