ESPOO 2008 VTT RESEARCH NOTES 2442

PRO

PRODUCTION

Operational decision making in the process industry

Multidisciplinary approach

VTT TIEDOTTEITA – RESEARCH NOTES 2442

Operational decision making in the process industry

Multidisciplinary approach

Teemu Mätäsniemi (Ed.)

ISBN 978-951-38-7222-9 (soft back ed.)
ISSN 1235-0605 (soft back ed.)

ISBN 978-951-38-7223-6 (URL: http://www.vtt.fi/publications/index.jsp)
ISSN 1455-0865 (URL: http://www.vtt.fi/publications/index.jsp)

JULKAISIJA – UTGIVARE – PUBLISHER

VTT, Vuorimiehentie 3, PL 1000, 02044 VTT
puh. vaihde 020 722 111, faksi 020 722 4374

VTT, Bergsmansvägen 3, PB 1000, 02044 VTT
tel. växel 020 722 111, fax 020 722 4374

VTT Technical Research Centre of Finland, Vuorimiehentie 3, P.O. Box 1000, FI-02044 VTT, Finland
phone internat. +358 20 722 111, fax +358 20 722 4374

VTT, Tekniikankatu 1, PL 1300, 33101 TAMPERE
puh. vaihde 020 722 111, faksi 020 722 3499

VTT, Teknikvägen 1, PB 1300, 33101 TAMMERFORS
tel. växel 020 722 111, fax 020 722 3499

VTT Technical Research Centre of Finland
Tekniikankatu 1, P.O. Box 1300, FI-33101 TAMPERE, Finland
phone internat. +358 20 722 111, fax +358 20 722 3499

Technical editing Anni Repo

Edita Prima Oy, Helsinki 2008

Operational decision making in the process industry. Multidisciplinary approach [Operatiivinen päätöksenteko prosessiteollisuudessa. Monitieteellinen lähestymistapa]. Ed. by Teemu Mätäsniemi. Espoo 2008. VTT Tiedotteita – Research Notes 2442. 133 p. + app. 5 p.

Keywords decision making, operation, maintenance, process industry, information management, measurement, optimization, uncertainty, fault isolation, fault diagnosis, collaboration

Abstract

The publication introduces a multidisciplinary approach to operational decision making (operation and maintenance) applied to the Finnish pulp and paper industry. The purpose of the approach is to produce knowledge and methods that support each other and which can be used to improve the support of operational decisions in the declared scope.

After a general level introduction to current trends and challenges in the research domain, operational decision making is considered from several viewpoints. Each viewpoint analyses the current practices and provides means for improving the decision support. The analysis does not attempt to be fully coherent but, instead, provides new pieces of information which are relevant to the overall understanding of the requirements of effective operations' decision support.

The normative view on operational decision making, introduced in Chapter 2, is based on statistical decision theory. It considers a decision task as an optimisation problem, typically with multiple objectives and uncertainties, and provides a fundamental set of decision making elements.

Chapter 3 presents a process monitoring and diagnostics view on operational decision making and describes new data analysis techniques for condensing and combining data. The new methods improve understanding of the process behaviour. The chapter also introduces performance measures for maintenance.

Chapters 4 and 5 deal with the organisational aspect of operational decision making. Chapter 4 considers the possibilities and constraints of human actors. Chapter 5 introduces a collaboration view on operational decision making that considers distributed decision making in human actor networks.

New standards, technologies and their assignment in a new proposed IT architecture are presented in the Chapter 6. In addition, the information technology development path, from current information systems to new ones, is described.

Chapter 7 concludes the publication by linking the themes described in the earlier chapters. It represents a way to establish a shared ontology relevant to stakeholders and decision support systems designers. This joins together the different roles and competences of the multidisciplinary approach.

Finally, a summary is given on the feasibility of the integrated approach and the future research needs in the field.

Operational decision making in the process industry. Multidisciplinary approach [Operatiivinen päätöksenteko prosessiteollisuudessa. Monitieteellinen lähestymistapa]. Toim. Teemu Mätäsniemi. Espoo 2008. VTT Tiedotteita – Research Notes 2442. 133 s. + liitt. 5 s.

Keywords decision making, operation, maintenance, process industry, information management, measurement, optimization, uncertainty, fault isolation, fault diagnosis, collaboration

Tiivistelmä

Tämä julkaisu esittelee monitieteellisen lähestymistavan operatiiviseen (operointi ja käynnissäpito) päätöksentekoon. Sovelluskohteena on suomalainen paperi- ja selluteollisuus. Lähestymistavan tarkoituksena on tuottaa uutta tietämystä ja menetelmiä, joilla voidaan tukea operatiivista päätöksentekoa ja parantaa päätöksenteon tukijärjestelmiä.

Aluksi esitellään teollisuudenalan nykytilanne ja muutostrendit, minkä jälkeen käydään läpi valitut lähestymistavat (normatiivinen, monitorointi ja diagnostiikka, ihmis- ja yhteistyönäkökulma ja standardi sekä IT-teknologiakatsaus) ja niiden tuottamat tulokset. Lopuksi kokonaisuutta esitellään esimerkin avulla.

Preface

This publication is a final report of projects Production2010 (Tuotanto2010, 1.2.2005–31.12.2006) and ProductionPro (TuotantoPro, 1.1.2007–31.8.2008). On the one hand, the purpose of the publication is to represent a coherent but critical vision of operational decision making and its support in the process industry. On the other hand, the publication summarises results of the mentioned projects and serves as an overview of more specific publications.

The Production2010 and ProductionPro projects (Business Driven Management of Operative Operations, Communication and Information Flows in the Process Industry) were established by Tekes – the Finnish Funding Agency for Technology and Innovation, Metso Corporation, Myllykoski Corporation, IBM Corporation, Stora Enso, Jyväskylän Teknologiakeskus Oy and Group Intelligentia Oy. Thanks to these companies for the financing, background material and interesting discussion they provided.

The following research partners and researchers have participated in the projects:

VTT Technical Research Centre of Finland:

Honkoila, Karri
Hukki, Kristiina
Mätäsniemi, Teemu
Pulkkinen, Urho
Paljakka, Matti
Ylén, Peter

Tampere University of Technology, Department of Automation Science and Engineering:

Grén, Juuso
Ihalainen, Heimo
Jokinen, Heikki
Konkarikoski, Kimmo
Pulkkinen, Petteri
Rajala, Miika
Ritala, Risto
Ropponen, Aino
Vesterinen, Teemu
Ylisaari, Johanna

University of Oulu, Department of Process and Environmental Engineering:

Ahola, Timo
Gebus, Sebastien
Holck, Päivi
Juuso, Esko
Launonen, Frans
Leiviskä, Kauko
Mäyrä, Outi
Sorsa, Aki
Tolonen, Teppo

University of Jyväskylä, Department of Mathematical Information Technology, Department of Computer Science and Information Systems:

Hakala, Antti
Heiskanen, Tero
Huumonen, Mikko
Kannisto, Esa
Kihniä, Johanna
Kämäräinen, Anna
Kärkkäinen, Tommi
Nurminen, Miika
Pekonen, Osmo
Saariluoma, Pertti
Suominen, Panu
Suvinen, Helena (Raija)
Valkonen, Tuomo
Äyrämö, Sami

Helsinki University of Technology, Department of Biotechnology and Chemical Technology, Department of Automation and Systems Technology:

Aarnio, Pekka
Cheng, Hui
Jämsä-Jounela, Sirkka-Liisa
Koskinen, Kari
Mattila, Marko
Nikus, Mats
Seilonen, Ilkka
Tikkala, Vesa-Matti

Thanks to all the researchers for their contributions to the projects and exceptional thanks to writers of the publication.

Tampere, August 2008

Teemu Mätäsniemi (Ed.)

Contents

List of abbreviations

APROS	Advanced Process Simulator
APS	Advanced Planning System
BI	Business Intelligence
BPEL	Business Process Execution Language
CBM	Condition-Based Monitoring system
CD	Cross-Directional control
CDG	Causal Digraph
CP	Counter-Propagation neural networks
CUSUM	CUmulative SUM
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DCS	Distributed Control System
DM	Data Marts
DSS	Decision Support System
DW	Data Warehouse
EAM	Enterprise Asset Management system
EDDL	Electronic Device Description Language
EIS	Executive Information System
EM	Expectation-Maximization strategy
ERP	Enterprise Resource Planning
FDI	Field Device Integration

FDT	Field Device Tool
GA	Genetic Algorithms
GDSS	Group Decision Support System
GR	Global Residuals
GUC	Generic Use Case
GURs	Generic User Requirements
IT	Information Technology
KM	Knowledge Mining
LIMS	Laboratory Information System
LR	Local Residuals
MD	Machine Directional control
MES	Manufacturing Execution System
MIMOSA	Machinery Information Management Open Systems Alliance
MOM	Message Oriented Middleware
MPC	Model-Predictive Control
ODSS	Organizational Decision Support System or Operational Decision Support System
ODSSs	Operations' Decision Support Systems
OEE	Overall Equipment Efficiency
OPC	OLE for Process Control
OPC UA	OPC Unified Architecture

OSA-EAI	Open System Architecture for Enterprise Application Integration
OWL	Web Ontology Language
OWL-QL	OWL Query Language
PCA	Principal Component Analysis
PCs	Principal Components
PIMS	Production Information System
PLS	Partial Least Square regression
PPCA	Partial PCA
PSO	Particle Swarm Optimizer
RDF(S)	Resource Description Framework (Schema)
RDQL	Query Language for RDF
SCA	Service Component Architecture
SDT	Statistical Decision Theory
SOA	Service-Oriented Architecture
SOR	Successive-Over-Relaxation-accelerated iterative Weiszfeld algorithm
SparQL	Query Language for RDF
SPC	Statistical Process Control
SuD	System-under-Development
SVM	Support Vector Machine
SWRL	Semantic Web Rule Language
UI	User Interface

UML	Unified Modeling Language
W3C	World Wide Web Consortium
WS	Web Service
XML	Extensible Markup Language

1. Introduction

By Teemu Mätäsniemi, VTT Technical Research Centre of Finland

This publication represents critically a decision making oriented vision of operational decision making and its support within the process industry. The vision is formed by studying several view points from several disciplines. The target of application is in Finnish pulp and paper industry and the presented results have been applied and tested in this context. The purpose of the publication is to make the reader aware of the current practices and lead him to a path where operative decision making processes are continuously developed. The document introduces a developed methodology and its rationale to approach operative decision making systematically. The publication is recommended for people who work at the management level or are responsible for information technology investments in process plants.

1.1 Research scope

Business processes are a set of coordinated activities of an organisation which are carried out to overtake a special organisational goal. Business processes can be characterised as depicted in Figure 1.1.

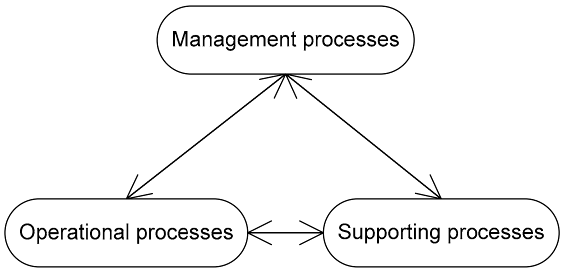


Figure 1.1. Business processes.

Management processes contain activities to control and develop other processes. Interesting management processes for this publication are strategic or tactical management, production management, service management, human resource management and information technology management. The role of management processes is seen as setting constraints to other processes.

Supporting processes consist of activities that support an organisation's core business. These kinds of activities include categories like accounting, recruitment and IT support. Those operational process activities which produce customer value are called core business activities. It has been observed that activities can change their location from one process to another process as the market situation changes.

In the pulp and paper industry, the core business processes contain production and maintenance tasks, such as grade change operations or equipment maintenance tasks, which are typically based on equipment and process monitoring today (Figure 1.2).

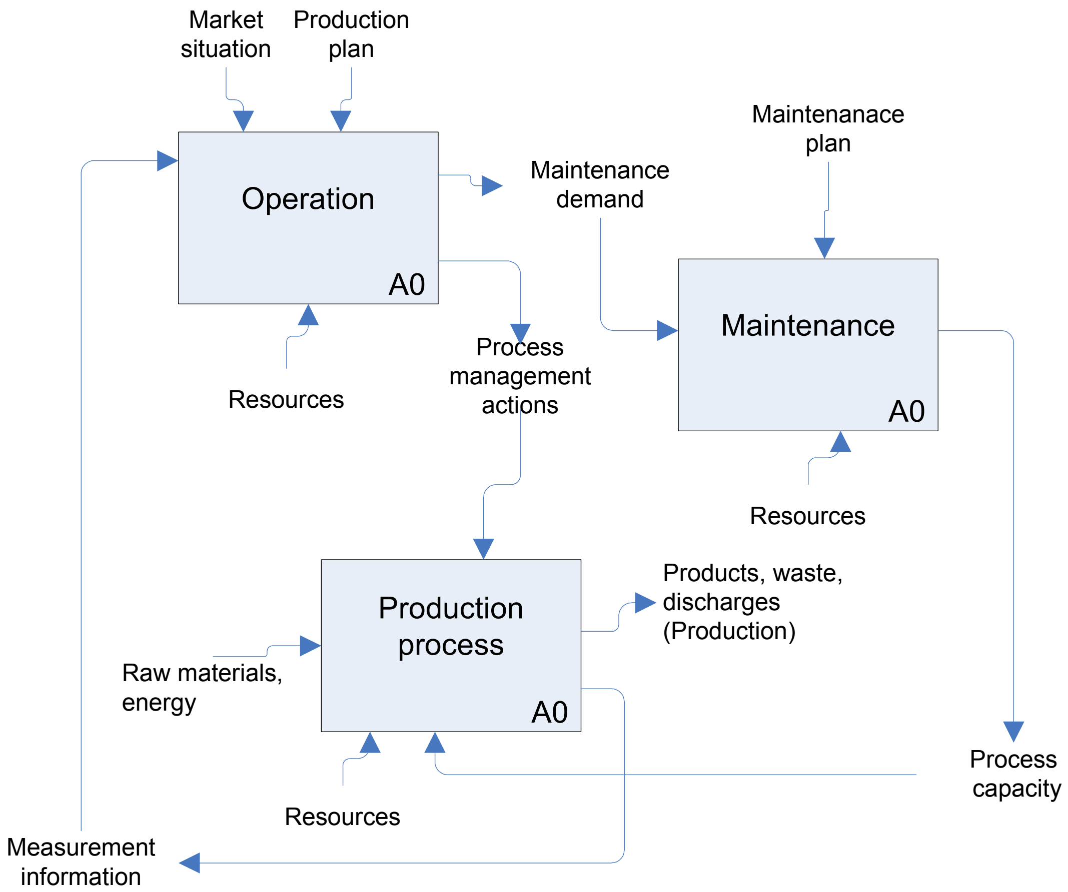


Figure 1.2. Operative tasks in the pulp and paper industry.

Production tasks, namely operation, are seen as functionality or activity whose decisions are realised as immediate production actions such as process control and machine operation. These actions can also include changes of connections or replacements of replacement units, components and tools as required by the product, process, etc. Thus, the operators are decision makers who make decisions to manage a production process. The main goal of operators is to combine the right mixture of production factors (raw materials, energy, know-how, time, physical assets) to manufacture, using the production process, products as effectively as possible.

Maintenance contains decisions about all the technical, administrative and managerial actions during the life-cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function. The main purpose of maintenance is to provide production capacity to operations. Thus, maintenance activity decisions have far-reaching effects on productivity and profitability.

This publication will approach these processes and their support from the following viewpoints: normative decision theory, data-based methods, knowledge mining tools and processes, organisational thinking, collaboration viewpoint and information technology.

1.2 Current working practices, decision making and support systems

In this section, the current status of operational and management processes, information utilisation and support systems are briefly discussed. More detailed discussion can be found later chapters.

The contemporary business environment has increased the strategic importance of the operation and maintenance function in the process industry because of its significant investments in physical assets. Regardless of this the current working practices on the operational level are fairly inflexible and task allocations are narrow, although minor changes can be seen. There are several reasons for current working practices, such as collective labour agreements, success of plants in the last decades and career advancement arrangements. The situation means that know-how about best practices is personalised and information exchange between actors or disciplines is insufficient. Inflexible task allocation affects workers who do not have a chance to react and prepare for external or unexpected changes. In addition, actions to repair abnormal situations are processed slower than in flexible organisations and, of course, the operations are more concerned about repairing existing problems rather than avoiding upcoming problems and improving current practices. All of these factors create the need for explicit shared understanding and task reallocation.

Even without disturbances, unexpected situations and current rapid production changes are challenging for operators, maintenance personnel and production planners who make decisions. Today, there is no systematic methodology to structure decision situations and to find out the relevant information and other needed factors in the process industry. The performance of decision making has been forgotten because in recent years a better competitiveness has been sought out from other factors, such as increasing capacity. Structuring the decision making situation means that all the relevant factors will be concerned, not forgotten, and action choices are found out and their effects will be evaluated. This kind of approach produces cost-effective decisions but it is not dominant today because of a lack of methodology and technology support.

The current information systems used to collect and store data produce a lot of information but the advanced data-based methods and knowledge mining tools are not widely used. Without these kinds of information processing methods, it is impossible for the human to understand and notice all the relevant dependencies in the complex operating environment. Additionally, the forthcoming decision making moment may not be noticed. To become more common, the advanced methods need a technology platform where data and its uncertainty are structured as information which can be retrieved seamlessly. In current systems, data and information lie in several subsystems and, to be useful, require transformations that cost too much because manual working phases are needed. Vertical and horizontal integration of subsystems and information is not at a suitable level. Business dynamic is increased but information systems are too rigid. In the current operation environment, the management actions need more realistic and real-time information about production state and changes in business environment. Respectively, operative actions need the information about upcoming production plans and quality feedback.

1.3 The operational environment: trends, challenges and a holistic conception

Nowadays, several research reports have been published that describe changes in the operational environment of the paper and pulp industry. These reports bring out challenges which should be kept in mind while researching new solutions to substantiate competitiveness for the Finnish paper and pulp industry. Trends are categorised as mega-trends and strong prospective trends in literature. A mega-trend is a phenomenon which is already a known and one which will continue in the near future as well. The scope of a mega-trend is global and its influences are also seen in societies. On the other hand, strong prospective trends have a shorter history and they are supposed to be alive some time but they do not interact with societies so substantially. Interesting and reported mega-trends and strong prospective trends for this representation are:

1. Meaning of know-how, creativity and innovations are emphasised in the future, especially utilisation of multidisciplinary know-how.
2. Environmental issues are more relevant in decision making and an image that an organisation works according to sustainable development principles has more market value.
3. Role of information technology is increasing.
4. Decreasing of labour in Western countries, especially in Finland.
5. New markets and new mass production plants in Russia, Far East and South America.
6. The process industry is moving from capital-intensive production systems to more agile, flexible and protean production systems.

Before linking these trends and their influences to a multidisciplinary approach to operational decision making, competitiveness is discussed.

Profitability is a prerequisite for the existence of all kinds of industry. In general terms, profitability is a company's ability to generate revenue from products and services that exceeds the cost of producing them. The costs consist of raw materials and other needed materials, such as minerals and chemicals, energy and the costs of process equipment, IT systems, labour and logistics. Profitability can be increased by increasing sales or decreasing costs. Increased sales mean more products or services to market or better margins from them. Respectively, decreasing costs means better cost competitiveness. There are many ways to consider factors of profitability. For this publication, issues related to decision making and its current challenges are concentrated on.

Today's situation and dominant trends generate boundary conditions and constraints on seeking out profitability in the near future. It can be said that there is no holistic conception of how the decision making related factors can be utilised to support operative decision making to generate additional value. There are only many questions, such as the following:

- Which kinds of decision making situations exist at the operative level?
- What is the role of the decision maker and an information system?
- Which information is relevant to the decision maker? What is the value of information?
- How can information be processed for and represented to the decision maker?
- How to train decision makers?
- When does a decision maker need the information?
- How to integrate different kinds of information? How to work with uncertainty?

To answer these questions and generate a holistic conception, a multidisciplinary approach is required. Figure 1.3 shows the decision making related issues of the holistic conception. The issues are used to explain positions and interrelationships of different approaches.

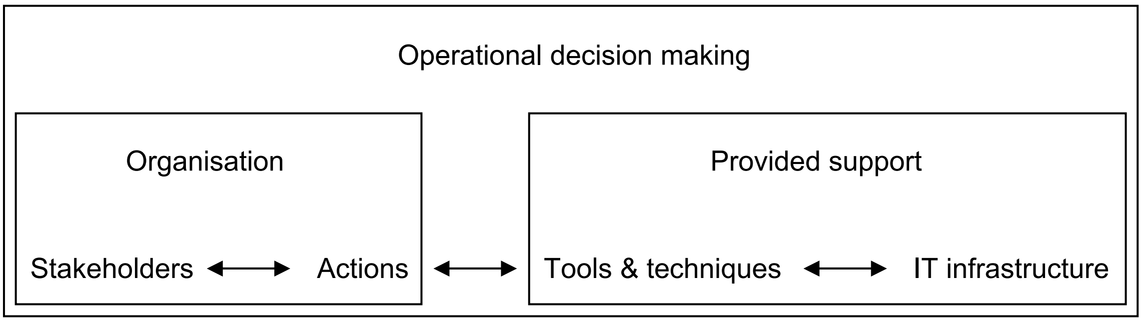


Figure 1.3. Decision making related issues of the holistic conception according to multidisciplinary approach.

Positions and interrelationships of different approaches are the following. The normative approach (Chapter 2) studies operational decision making as an activity and as a situation. It structures decision situations at an abstract level which aids in the interpretation of situations and in information system design. Computational methods and technologies (Chapter 3) are focused on tools and techniques. New techniques enable new kinds of actions to be performed and existing challenging actions need better methodological support. Decision making, launching actions and executing them are the responsibility of stakeholders. People also design and use information systems. Human dimension (Chapter 4) introduces the capabilities of the human as decision maker. The chapter addresses also the necessity of support systems in the operation of complex production systems. The collaboration view (Chapter 5) considers stakeholders as a network of actors. The study of stakeholders interrelates also with provided support because the skills of the users of a support system are different and, at least, indirect communication between stakeholders is enabled with technologies. The IT approach (Chapter 6) considers users and provides a platform for techniques. Use cases (Chapter 7) describe the implementation of a new support system in organisations.

The normative approach to operational decision making is introduced in Chapter 2. It is based on statistical decision theory. It considers a decision task as an optimisation problem, typically with multiple objectives and uncertainties, and provides a fundamental set of decision making elements. Structuring is represented at an abstract level so that it is applicable for different kinds of decision situations and flexible enough to respond to trends in the operational environment and the contribution of other disciplines. The profitability aspect of this view is included in the approach, enabling different decision making situations to be considered systematically and time-independently and thus forms a good base for collaborative understanding and development of information systems. In addition to fundamental decision making elements, the chapter introduces the phases of decision making process needed to structure decision situation. The relationship of these phases is emphasised while considering the state of system, applicable actions and effects of actions.

Chapter 3 describes new techniques for data analysis for condensing and combining data used in process monitoring and diagnostics. The amount of collected data in modern process automation environments has been growing explosively in recent decades. At the same time, the complexity of systems has increased while different kinds of networked solutions have emerged. The new methods improve the prediction of future process events on the basis of better understanding of the underlying process behaviour. Additionally, new tasks for process automation have emerged and new methods provide support for multi-skilled roles, flexible task allocation or in compensating for passing know-how, and for producing special products with more demanding processes. The methods also pave the way to managing the process more safely and improving environmental health. They bring forth interactions which may be impossible for the operator to notice early enough to avoid abnormal situations. Today's methods can handle larger data sets but they also need more processing power and extensive research to gain more ground in actual process applications. Thus, existing methods and the development of new ones increase investment costs, but make the more integrated monitoring of production and maintenance possible.

At the end of the day, the crucial decisions are always made by people. They design and use information systems and if we are unable to understand the human dimension of information systems it is difficult to realise and implement really effective systems. We have to understand how these systems are used optimally and how to get users to use them in the best way. Chapter 4 takes psychological problems and users seriously. It demonstrates the weaknesses of human decision making and the reasons for the difficulties people have in rational decision making. This part of the literature review can be seen as the basic justification for the development of the present type of information systems. The chapter also clarifies the following terms: decision making, problem solving and design thinking. People are fallible and they make biased decisions. Therefore, in situations as complex as industrial processes, it is necessary to have decision support systems. The chapter also discusses the implementation of such systems in practice. It emphasises how in designing a DSS it is essential to have a clear idea about how people should use it and how the new usage culture can be implemented. It is essential to have a clear training plan which continues a longer period of time, until even the rare usage problems are solved. The period enables cost-effective start-up of an information system.

The approach in Chapter 5 takes a collaboration view on operational decision making. Regarding decision making as distributed among a network of actors with interconnected tasks provides a useful framework for considerations of possibilities to promote shared understanding, unified working practices, multi-skilled expertise, explication of tacit knowledge and awareness of business strategies. The holistic and systemic perspective makes it easier to identify how work practices and IT system functionalities should be developed in order to be able to support distributed operational decision making in the enterprises.

Chapter 6 studies the question of what kind of support information technology can offer to decision making in the process industry in the future. The presentation is focused on the operations and systems at the manufacturing operations management level, i.e., between ERP and automation in the information system hierarchy of a company. The study of development starts from the existing systems. The requirements of both single decision maker and collaborative decision making may be reflected in their properties. With help of developing new information technologies, new information system architecture might be created, which would better fulfil the various requirements of decision making. In practice, changes to the information systems will be gradual. However, the development should be guided with a clear vision.

Chapter 7 covers all the relevant aspects of ODSS, establishing linkage between themes described in the earlier chapters by suggesting a new generic business use base, such as specifications for operational decision support systems, and a way (stereotyped entity model) to establish a shared ontology among relevant stakeholders. This joins together the different roles and competences of the consortium project participants.

Further reading

PSK 6201. 2003. Maintenance. Terms and Definitions. 2nd edition. Helsinki: PSK Standards Association. 30 p.

2. Normative decision theory as a framework for operational decision support

By Risto Ritala, Tampere University of Technology

Normative decision making considers all decision tasks as optimization problems, typically with multiple objectives and uncertainties. Therefore in normative decision making the decision tasks must first be formulated mathematically and then the resulting optimization problem is solved. Normative decision making does not claim objectiveness in decision making: in particular, the optimization goals and constraints, and the attitudes towards uncertainties express decision makers' subjective references. However, once the optimization problem has been formulated, choosing the action is a mathematical operation and hence normative decision making is a rational deduction.

In this chapter we do not claim that all practical operational decision tasks can be mathematically formulated, and definitely not all that can be formulated can be numerically solved in a reasonable amount of time. The idea is that normative approach provides a framework of decision making elements and sets a long term quest of continuously developing the formulation of each decision task and the methods for solving the problems.

The normative approach in this chapter is based on the Statistical Decision Theory (SDT). We will discuss, in particular

1) how the link between business requirements and operative objectives can be made explicit
2) how the normative approach to operations and related decision making establishes a basis for rigorous operations' decision support under changes within organizations and in their goals, or when operational tasks are redistributed between personnel
3) how an abstract set of user requirements (to be referred to as Generic User requirements, or GURSs) link IT infrastructure, methods of data analysis, optimization tools, and communication between the system and users and among personnel; GURs are organized according to the mathematical structure of SDT
4) although human decision making is analyzed in detail in Chapter 3, the interface between normative and descriptive decision making is shortly discussed in the context of industrial operations.

This chapter is organized as follows. Section 2.1 discusses how operations can be analyzed as a set of tasks for the organization to carry out. The main claim of the normative approach is that rationality in decision making is an overriding virtue, given a fixed set of business goals. Section 2.2 analyzes the present decision support systems for operational tasks. Section 2.3 analyzes the normative approach as a remedy for shortcomings in the present decision support systems, pointed out in Section 2.2. In Section 2.4 the structural elements of SDT are introduced without mathematical rigor. Finally Section 2.5 discusses the elements of SDT as a basis for decision support implementation. Defining a set of GURs according to elements of SDT and then implementing decision support functionality guided by these GURs is suggested. A preliminary set of GURs is given as Appendix A.

2.1 Operations decision making: linking business strategy and daily operations

The scope of the work described in this chapter has been supporting operative decisions at production industries with the papermaking industry as a specific example.

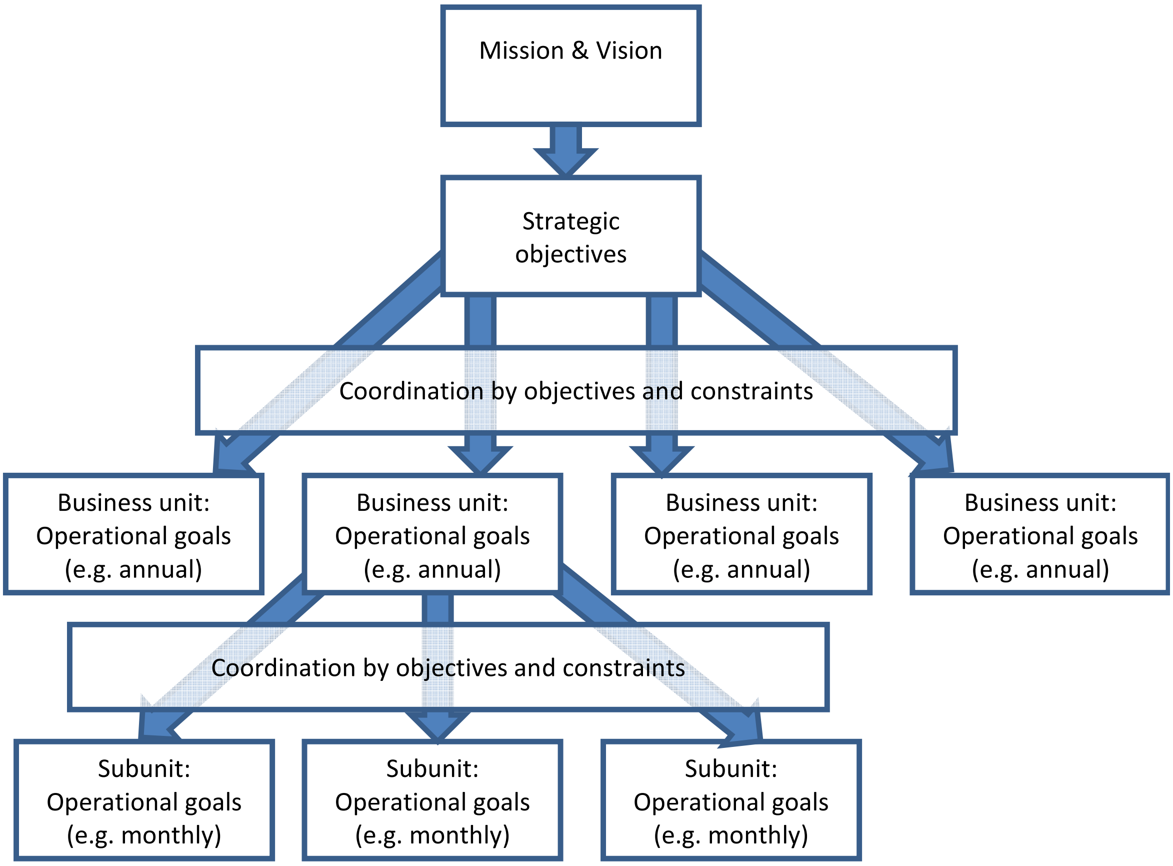


Figure 2.1. The operational goal setting ideally is a transparent objective hierarchy derived from company vision and mission. However, the link between strategy and daily objectives may be obscured by the fact that at each management level the operational objectives have a coordinating component in addition to a strategic component. In the normative approach to operations' decision support the strong assumption made is that the operational goals are expressed clearly enough to serve as the basis for rational decision making.

Figure 2.1 illustrates the goal-setting mechanism in an organization. Definition of business vision is a task for the shareholders and the board of directors. In a public company the management typically makes a proposal of the strategic objectives for the approval by board of directors. On the basis of strategic objectives, the company management sets the operational objectives. The goal of operational objectives is usually two-fold: not only do they promote directly achieving the strategic objectives, but they also are a means of coordinating activities throughout the organization. With such coherence achieved the strategic objectives are enhanced beyond optimizing the operations at each operational unit.

The operational objectives are expressed both as goals, and as constraints on how the operations may be carried out. Constraints usually have a coordinating role amongst units. Coordination may occur at many levels. The production planning and scheduling of units is constrained for the benefit of the entire company, although such constraints reduce the profitability – the main goal set by the company – of an individual unit. Within a paper production line, the operations of pulping and papermaking are constrained to prevent greedy profit maximization – usually in terms of internal transfer prices – in one of the operations. Control actions on, say, cross-directional variations of basis weight and moisture may need constraining in order to achieve a reasonable balance between the two and to prevent fluctuations between variations of the two quality parameters.

The business mission and vision of a company are quite permanent. They position the company amongst business branches and within its main branch. The business vision is usually changed only through a crisis, and when changed, the company is reborn.

Strategic objectives are usually set for 3–10 years and they tend to be strongly coupled to the persons in top management. A major change in strategic objectives means that the company attempts to achieve its business vision through a radically changed approach. As a result of change in strategic objectives the company organization – including top management structure – is thoroughly restructured.

Operational objectives are under continuous revision in today’s companies. The management attempts to achieve the strategic goals through operational objectives and constraints, but the responses to these objectives and constraints are often complex. Thus it is the key duty of the management to continuously evaluate the performance with respect to strategic objectives and to tune the operational objectives accordingly. In conjunction with tuning objectives the management often chooses to tune the operational organization as well, which means regrouping operational tasks into new job responsibilities and reallocating personnel to job positions. Hence the environment of operational decision making is highly dynamic and any system support must be able to quickly adapt to changes in goals, objectives and organizations.

We limit the scope of this chapter with the following four definitions:

1) We assume that the operational objectives and constraints are given, as in Figure 2.1, but they are expected to vary over time.
2) The operations are a time-critical activity in that not making an operative action at any given time instant cannot be fully compensated at a later instant.
3) The production is operated on the basis of information history which consists of history data and the knowledge base of the operating personnel.
4) The production is operated as a group effort of operating personnel, yet with structured job responsibilities that are expected to change over time.

We shall take the abstract point of view of operations by stating that operations can be structured into tasks, each with their specific decision making process. Such a structure can be identified e.g. with business process re-engineering targeted to production. Hence the entire operation of production is a portfolio of tasks, see Figure 2.2. The benefit in this point of view is that it is quite robust both when the objectives/constraints of operation or when the way how the tasks are allocated to the personnel is changed. However, at any given time there is a well-defined distribution of the task portfolio to the operating personnel, which defines the needs of person-to-person communication and system-to-person communication. In the task portfolio model the person-to-person communication needs may be analyzed as task-to-task communication needs with the capabilities of the persons responsible for the tasks taken into account.

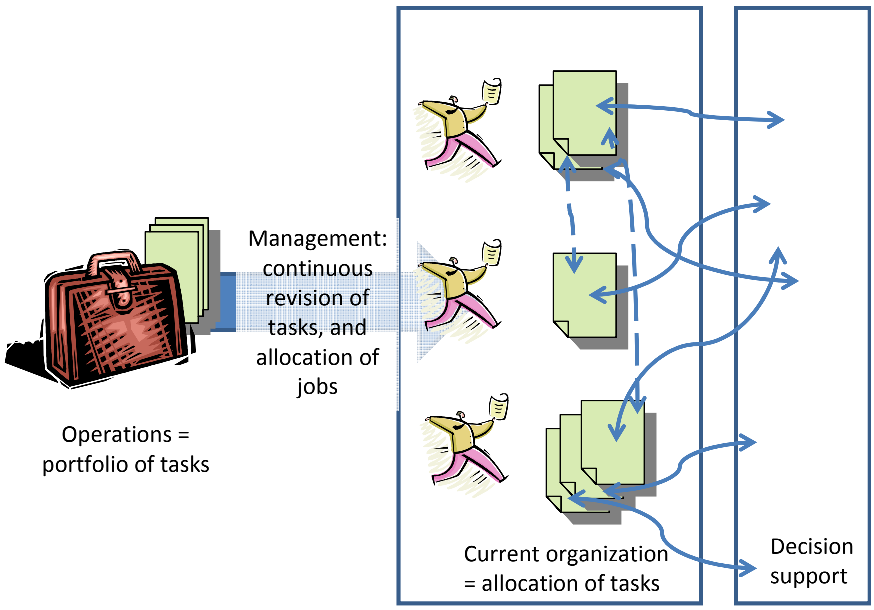


Figure 2.2. Operations as a portfolio of tasks. When decision support is structured according to the tasks rather than job descriptions, the system is robust against organizational changes are made. Need of support and person-to-person communication is via support and communication needs of tasks.

The decision making related to a given task in the portfolio is a group effort. We limit the scope of this chapter to cases where one person in the group is the responsible decision maker and the other members of the group have the role of experts: they provide their motivated opinion about the decision and assist the actual decision maker in understanding all the effects of the potential actions. This is the dominating practice of group work in Finnish process industries. Thus we exclude genuine multi-decision-maker situations in which the decision is made through some voting mechanism, explicit or implicit. In some process industry cultures the group decision making works strongly towards reaching a consensus. Even in such cases there usually exists a single person responsible for the decision made and hence this could be viewed as a version of our model of decision maker supported with experts. However, it is expected that decision making through consensus building requires support somewhat different from the decision-maker-with-experts model. We leave the specific features related to consensus building outside the scope of this chapter.

The operational task consists of the following subtasks:

1) detecting the need for taking an action
2) comprehending the present state of the operation
3) comprehending the set of potential actions
4) comprehending the consequences of each of the actions
5) evaluating the consequences with respect to given operational objective(s) and constraints
6) choosing the action with the best predicted consequences
7) implementing the action
8) monitoring the consequences of the action in order to detect possible further needs for actions.

Within these tasks there typically are decisions/actions about communication. In order to comprehend the present state, potential actions and their consequences the decision maker retrieves data both about the most recent development of the system and about situations similar to the present one that have occurred sometime earlier in the operations history. The decision maker may decide to acquire further data and other information before making the decision about the action: expected benefits of this further information outweigh the cost of delaying the decision. Furthermore, the decision maker consults with her/his experts on the present state, potential actions and the consequences. When operational objective and constraints are ambiguous or when the relative importance of the many components in the objective has not been assigned in an unambiguous way, the decision maker consults her/his experts on interpreting the given objective.

We define the operations' decision support systems (ODSSs) as mathematical IT-based tools that assist the operating personnel to carry out their tasks better, when evaluated according to the operational objectives and constraints on operation derived from strategic business goals. Within the scope of normative decision making and operations as a task portfolio the research results presented in this chapter seek to reengineer the operations decision support systems (ODSS). We assume that objectives for the operation of production, and hence for ODSS, have been defined as a result of a strategic action. The re-engineering formalizes operational decision tasks to some degree, but we take into account – to be realistic – that mathematical formalization is incomplete, and the formalization degree varies from task to task.

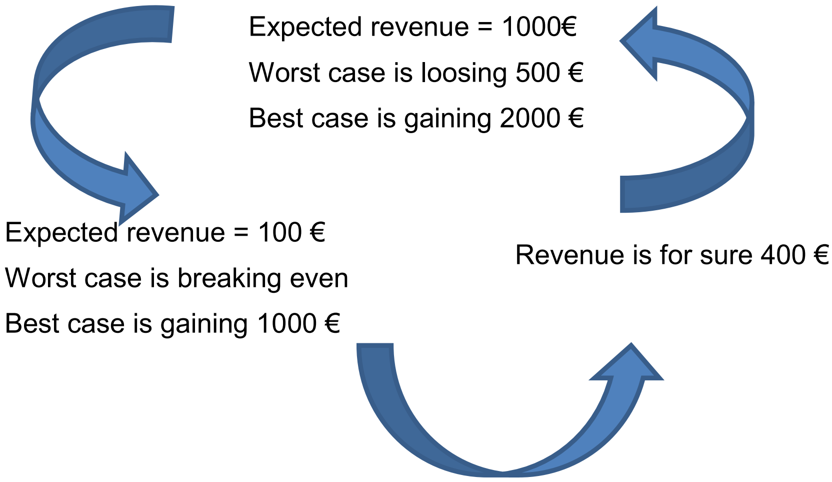


Figure 2.3. An example of circular preferences in irrational decision making, e.g. the tail end of the arrow is preferred to the head end. A person may end up at such irrational preferences that she/he is uncertain how to value risk over expected profit.

We assume that the operations decision making should be rational in a specific way: if three actions A, B and C are presented in pairs, the decision maker may not end up with circular preferences, such as A is better than B, B is better than C and C is better than A, Figure 2.3. Although this may appear as a trivial assumption, human decision making analysis has shown that rationality easily breaks down, in particular when the decisions have multiple objectives or there is considerable uncertainty about the outcomes. These aspects of human decision making and their consequences for ODSS development are discussed in Chapter 4.

2.2 Critique on state-of-the-at ODSSs from normative perspective

History data bases with advanced search functions, case study document databases, process data analysis systems, production diaries with data and data analysis linking possibilities, case-based reasoning systems, expert systems – crisp or fuzzy – are example of technologies on which present ODSSs have been developed.

The present ODSSs are generally considered to provide rather poorly the expected decision support. ODSSs have developed in an evolutionary way, which rather often means that they are unstructured or structured in way not supporting a systematic approach to decision making. The scope of ODSSs tends to be incrementally widened, which also results in complex structures and a non-uniform approach to decision making.

ODSSs are expressions of knowledge within the organization, as their goal is to distribute best practice to decision making. Unfortunately, when present systems have been developed, the thought risks of the experts describing the best practice have not been fully appreciated. Examples of such thought risks are:

1) neglecting new evidence that is contradictory to established beliefs
2) specializing the (mental) model to extreme cases
3) in hindsight, assuming the predictability of an event or situation to be higher than it actually is
4) failing to recognize that a poor action only by chance resulted in a good consequence
5) failing to comprehend the uncertainty in expert knowledge.

Such thought risks may be realized both at the implementation phase or when using the system. They may occur independently of whether the system is implementing the decision support for best practice in heuristic terms (crisp and fuzzy rules) or in quantitative mathematical models. Although on surface mathematical models may appear more robust with respect to thought risks than rules, the risks are often realized as an inappropriate choice of model structures, over-fitting the parameters, selecting irrelevant data for model identification, inappropriate model updating/adaption and selecting biased priors.

The present ODSSs do not express or analyze explicitly the uncertainty about the knowledge, (mental) models, or data. In particular, in financial mathematics and in related psychological analysis of decision making, the uncertainty about consequences has been found to be an important element of decision making when the consequence uncertainty of the potential actions varies greatly in magnitude or in distribution. Furthermore, the uncertainty is the key to dealing with and merging information about a target obtained from several sources. In operational decisions beyond simple control tasks the uncertainty of consequences of potential actions is typically varies largely from action to action.

The user interfaces of many ODSSs do not fully appreciate that the decision maker supported may need an explanation of varying degrees of details and different ways of reworking the decision about the task. Most ODSSs either provide the decision maker raw data related to the decision or a decision candidate with little justification.

The ODSSs support poorly the interaction between the decision maker and her/his experts. Each group member collects her/his data and links that to their mental models but feeding the revised knowledge back to the system and reworking that to a decision is not covered.

The links between the functions of ODSSs and the operations' tasks are rather obscure, and hence the beneficial use of ODSS requires deep understanding of the ODSS itself. The ODSSs are rather complex to use and learning about them takes some time. Hence the utilization of an ODSS is vulnerable to personnel changes. There are many cases in which a system actively used has become obsolete simply as a result that the main system user has left the organization. When an organization is restructured and hence decision tasks redistributed, the persons applying the ODSS will be different, again leading to a critical instant for ODSS use and utilization.

2.3 The concept of normative decision support

The next generation normative ODSSs should solve many of the shortcomings of present ODSS, as criticized above. Furthermore such ODSSs should be an assisting tool when continuously developing the decision making beyond present best practices by gradually structuring and formalizing decision tasks into optimization problems and then reallocating operational tasks. Hence the vision about normative ODSS encompasses also the organizational aspects of implementing and utilizing ODSS.

We seek that ODSS is an integral part of the development of performance and competence of the operations organization. Hence the ODSS is designed with a systematic life cycle management policy which includes the implementation phase, the evolutionary development through knowledge and scope updates, and the changes in the production system and organization. Thus it may be adapted to more revolutionary changes in production assets and organization as well, in particular to major redistribution of operational tasks amongst job descriptions.

There are four key elements in the vision of normative ODSS that are crucial for systematic life cycle management and continuous improvement of decision making practices.

First, the paradigm of operations being a task/decision portfolio is taken as the structural model of the ODSS and the elements of the formal statistical decision theory (SDT) are chosen as the way of describing each of the task/decision components in the operations portfolio. This does not, however, imply that all the task/decision components can be fully described as SDT problems, but the user is guided to think of the problem through specifying such SDT elements. The SDT elements are introduced in Section 2.4.

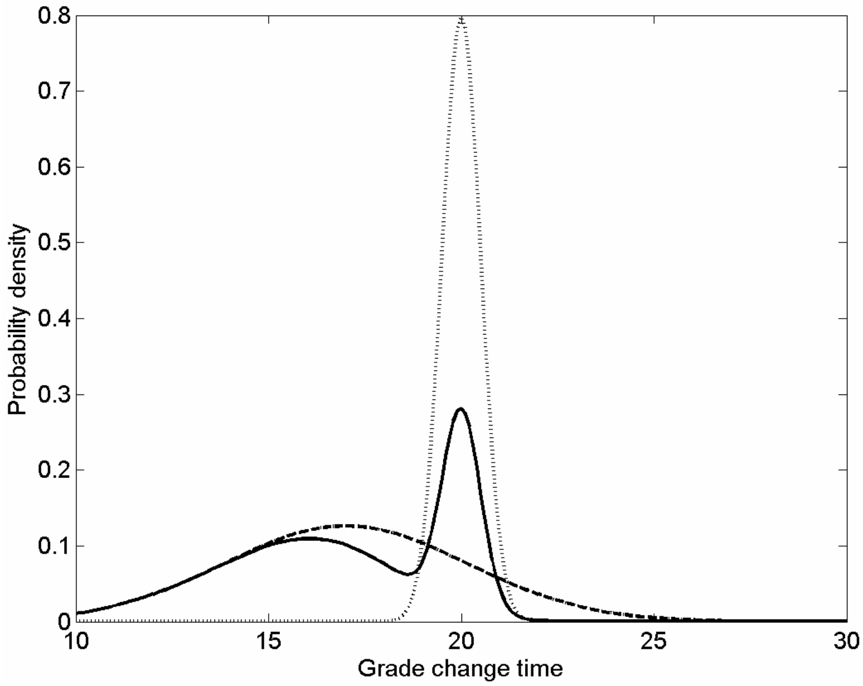


Figure 2.4. An example of a decision situation at which the uncertainty may be an important factor. Three predicted consequences of grade change actions with full distributions describing the uncertainty: an option with short expected grade change time but with high uncertainty (solid line), an option with high expected grade change time but small uncertainty (dotted line), and a compromise option (dashed line). Judged by expected grade change time, the high uncertainty case would be favoured whereas practical decision makers may prefer the compromise option that eliminates long grade change times and gives a good expected grade change time, or even the highest expected grade change time because of its good predictability.

Second, the uncertainty in state information and about predictions is made explicit for the decision maker. This is highly challenging for two quite different reasons: the present IT infrastructure does not support propagating uncertainty metadata along with the data, and operations personnel is not accustomed to dealing with uncertainties. However, if uncertainties are neglected, a main factor affecting complex decisions is lost and the resulting performance of decisions and hence that of operations is severely hampered, see Figure 2.4. Uncertainty is described exactly only by probability densities, which in the most general case is computationally intensive and consumes storage capacity. When uncertainties can be approximated with Gaussian distributions, the description reduces to covariance matrices or variances that are computationally simple and can be readily applied in optimization. In some cases uncertainty is hard to estimate even roughly, and some upper estimates based on domain knowledge or general considerations must be applied. It is of particular importance that model predictions about consequence actions may strongly depend both on present state estimates (data) and on the action considered.

Third, mechanisms to avoid thought errors both at the initialization phase and during continuous use of the ODSS are considered. As tackling uncertainty explicitly is a novel component of the next generation ODSS, mechanisms to avoid thought errors related to uncertainties and probabilities are in focus. The mechanisms implemented fall into two categories: automatic detection of contradictory/biased elements when decision makers are analyzing their task, and mechanisms raising awareness of the risk of thought error.

The fourth key element is the ODSS's capability of supporting cooperation of personnel, the decision maker and her/his experts. Through the approach structured by SDT elements, the group may work as a team, in populating the elements, and discussing and reviewing them. This is the more important the less ready-instantiated structure there exists for the task.

The next generation normative ODSS will develop the decision making at three levels. First, the decisions are carried out on as-is basis, but the system will collect the best practices and thus homogenize behavior of similar tasks. Then the system with normative approach will help with identifying and eliminating risky practices in decision making. This is because setting up support for a particular task necessitates descriptive decision analysis: decision biases and thought risks are more easily observed. Finally the ODSS will help identify poorly structured repetitive tasks. For example, the normative decision analysis based on SDT will provide a check-list for such tasks.

This gradual and stepwise development is similar to the one experienced in paper quality control during 1980–2000. For example, cross-directional basis weight was considered as a task for highly skilled operators in the late 1970s. The role of the measurement system was to inform the expert, who then explained the correct procedures to novice users. The action response analysis was gradually developed by studying the expert users and by obtaining measurement data. With response model the operators could first test action setups with computational tools before trying them out at the machine, so that obvious thought risks were identified before implemented. With response models optimized action setups could then be calculated and suggested for the operators. Eventually cross-directional basis weight was implemented in a closed loop. However, there are many paper properties which must be managed in cross direction, and in the mid-1990s the first tools were developed for analyzing the trade-off between cross-directional variations in the key quality parameters. There remains several incompletely structured operational tasks related to cross-directional control: e.g. how to ensure the quality of cross-directional variation estimate (CD/MD separation problem), how to manage the effects of cross-directional web shrinkage on consequences of action setups, and along which path to measure with the scanning sensor.

There is a strong interaction in development of ODSS and that of the organization. ODSS will set requirements to the organization but it also provides guidelines on how to conceptualize the operations. The interaction is at structural, competence and individual levels.

With the straight forward portfolio paradigm of operational tasks/decision, ODSS clarifies the operation and procedures in that it unifies the practices between teams – shifts – having the same sets of tasks. The portfolio paradigm enables new operational practices, in particular by enhancing cooperation aligned according to the interaction required in tasks. The structuring of operations into tasks may open up opportunities to organize the tasks in a completely new way.

ODSS is a representation of knowledge within the organization. Clear task template structure in ODSS may ease explicating the tacit knowledge and hence improve organizational learning. Knowledge management has been considered as an activity with high economic potential for organizations, but so far it has delivered very little of this potential. Knowledge management systems have been rather unstructured. The strictly structured approach to ODSS proposed here is an approach orthogonal to present knowledge management systems. Although the strict structure may set some thresholds for recording the tacit knowledge, once structured, the knowledge is in an operational form and thus easy to exploit.

For the individuals within the organization the next generation ODSSs provide quicker uptake of best practice, improved comprehension of tasks and roles within the organization and better understanding of the strategic objectives of the organization.

It is clear that implementing the next generation ODSS requires a consorted training program. The concepts in the decision structure, how uncertainty is to be interpreted in decision making, what are the thought risks/errors, and how they affect decisions, all require deepened understanding and thus training. Intense cooperation through ODSS is also a quite new way of working and hence requires a lot of testing and simulation.

2.4 Elements of Statistical Decision Theory (SDT)

Statistical Decision Theory (SDT) is a mathematical theory on how to make rational decisions when there is uncertainty in consequences of potential actions and such uncertainties may vary greatly from action to action. Fully structured SDT is a deterministic optimization problem with an objective, constraints, and system and observation models. In this section we assume that this is a single-objective problem. In practice, operational decision tasks may often be of multi-objective nature. The multi-objective extension of

SDT is analogous to extending regular single-objective problems to multi-objective ones, once the objectives have been formulated according to practices of SDT.

2.4.1 Key descriptors

The key descriptors of SDT are *state*, *measurement*, and *consequence*. *State* is a unique description of the current status of the target system. State is not directly observable, but we obtain *information* about it through *measurement data* and earlier experience. *Measurement* is a means of providing measurement data that is informative about the state, regardless of the form of the data (numerical, binary or textual). Information is here understood in the sense of information theory: based on all the measurement data and earlier experience, the available information assigns probabilities (probability densities) to state values according to how likely the state is to be at that value. Often a practical description of the information is in terms of Gaussian distribution. Then the mean value is referred to as the *state estimate* and the (co)variance (matrix) as the *uncertainty of the estimate*[1]. *Consequence* is a collection of attributes by which we judge the success of action made. Consequence is typically a mapping of system state to some low-dimensional value space when a set of actions are considered.

The set of potential *actions* is the descriptor setting the degrees of freedom for the decision maker.

Figure 2.5 illustrates the key descriptors and their relationship in decision making.

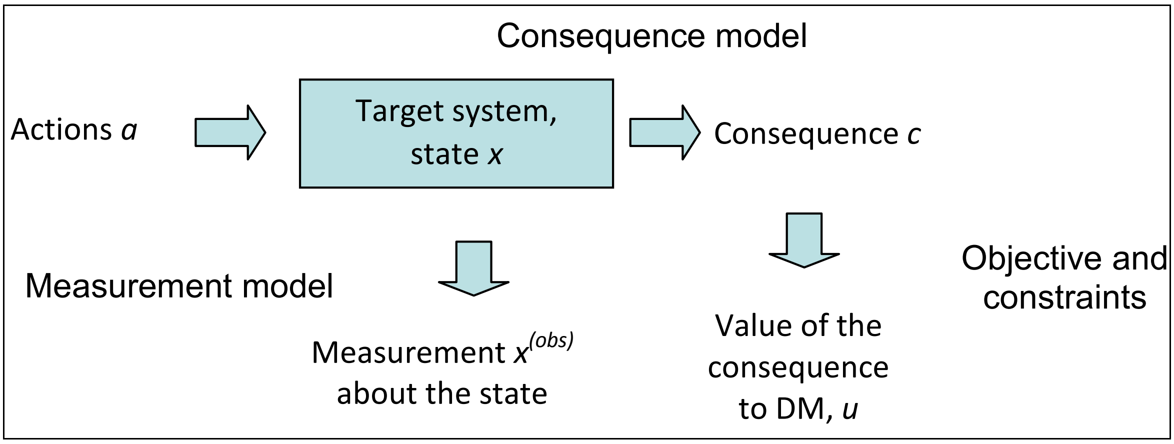


Figure 2.5. The key descriptors of the decision making problem and their relationship.

[1] Contrary to common practice we refer to uncertainty as *variance* of random variables rather than *standard deviation*. This is because in multivariate cases with correlated uncertainty, the standard deviation does not have a natural counterpart.

2.4.2 Models

SDT requires two models: a *measurement model* and a *consequence model*. Both the models are expressed as conditional probabilities.

The measurement model assigns at each possible state of the system the probability to obtaining a given measurement result. Quite often the statistical variations of different measurements are not correlated and then the overall measurement model decomposes into a collection of individual measurement models for each measurement device (or other information channel). However, it should be noted that e.g. common sampling for measurement devices tends to lead to correlated statistical variation and then decomposition is not appropriate. If the measurement model is a Gaussian distribution and the measurement is about a state component, the mean value of *unbiased measurement* is the actual state value and the variance is called *measurement uncertainty*.

A new set of measurement values translates to information about state through Bayesian principle that combines measurement model and any *pre-existing information* about state. Such pre-existing information may originate from earlier measurement data or from other sources, including the process knowledge of personnel. Kalman filtering and its extensions are systematic and powerful computational tools in utilizing optimally the pre-existing information in earlier measurement data.

Consequence model assigns a probability to ending up at a consequence when a given action is made at a given state. It is quite clear that the consequences of actions cannot be predetermined even if the state at which the action is made were exactly known. Hence consequence models are inherently probabilistic. There is a huge arsenal of modeling methods suitable for consequence models – ranging from first principles models to statistical black box models, and from simple linear-Gaussian models to complex nonlinear models. These methods are discussed in detail in Chapter 5. All these models are capable of providing the probabilistic nature of the model by describing the statistical deviation between their predictions and observations from the target system in Bayesian terms. However, such uncertainty analysis is not a common practice in all these paradigms, e.g. in conjunction with first principles models *model validation* is rather the concern than model uncertainty analysis. Fuzzy models are inherently different from other modeling paradigms in that the approach to uncertainties is through granularization of state values rather than uncertainties in model structure or parameters.

2.4.3 Objectives and constraints

Let us assume that – were there no uncertainty – the decision maker would seek to maximize one of the consequences. Let us call this consequence the *primary objective*. With the measurement and consequence models and pre-existing information it is possible to calculate the probability for each value of the primary objective for any given potential action, see Figure 2.5. In general, different actions may lead to consequence probability distributions differing vastly in terms of uncertainties as was shown in Figure 2.4. Hence the decision maker is choosing between probability distributions, a task that has proven to be extremely complicated in all areas of decision making.

A straight forward approach is to choose the action that provides the maximal expected value of primary objective, thus neglecting the possibly differing uncertainties of action alternatives. Such an approach is called *risk-neutral*. Risk-neutral decision making may be well justified when the decision task is frequently repetitive: even though the action chosen would have an exceptionally wide consequence probability distribution, the occasional poor values of the primary objective will be balanced by exceptionally high ones in the long run.

If the decision making favors large uncertainties, it is called *opportunistic*. Participating in a lottery is an example of opportunistic decision: on the average money is lost, but with a tiny probability a large amount of money is won. Generally industrial operational decision making is either risk-neutral, or favors alternatives with small uncertainties, which is called *risk-averse*, see also discussion of Figure 2.4.

However, as the consequences of actions are known only probabilistically and therefore the decision maker is choosing between probability distributions, the attitude towards uncertainty is an element in operational decision making. At present the attitude of decision makers, such as process operators and engineers, towards uncertainty is intuitive. This often leads to that two decision makers with exactly the same "facts", i.e. measurement data, consequence model and primary objective, end up at different decisions. Obviously this leads to confusion within the organization. Explicating the uncertainty in operational decision making can be considered one of the key tasks of a normative ODSS. With explicit analysis of uncertainties, a joint attitude towards uncertainty may be derived. We claim that attitude towards uncertainty in decision tasks is a strategic decision itself and should not be left for the individual decision makers, if consistent and rational operation is to be achieved.

There are several ways to derive the SDT objective given the primary objective and attitude towards uncertainty. Theoretically the soundest approach is the *utility function* that maps any probability density of primary objective to real numbers. It has been proven mathematically that for a rational[2] and consistent decision maker there exists a utility function – unique up to scaling and biasing not affecting which action is chosen – such that the optimal decision is the one maximizing the *expectation value of utility function*. This is remarkable as it reduces the comparison of probability distributions to comparison of numbers.

There is a general method for identifying the decision makers' utility function through a set of questions, such as "given a consequence A for sure, or alternatively uncertain consequence such that B occurs with probability p and consequence C with probability (1-p), what should p be so that the alternatives are equally good". Obviously, such questions are rather demanding and hence identifying the decision maker's utility function in practice has proved to be a complex task.

Attitude towards risk can also be expressed as *maximizing the expected primary objective under additional constraints*. For a risk-aversive case such constraints limit the probability of exceptionally poor consequence. There is no general methodology for how to set up these constraints by analyzing or questioning the decision maker, but the constraints must be set by her/himself, which requires a rather deep understanding of the concepts of both probability and constraints in optimization, and – obviously – a detailed understanding of the strategic objectives.

There are also heuristic ways of describing attitude towards risk. One example is the *risk premium* which states that the objective is to maximize the expected value of primary objective plus/minus (opportunistic/risk-averse) a term proportional to the standard deviation of primary objective. Risk premium is widely used in financial applications, such as stock pricing.

If there are other consequences than primary objective, these are for constraining the decision problem. As these *secondary objectives* are given in terms of probabilities, the corresponding constraints are constraints for their expectation values, variances, and other forms of the distributions. If the primary objective and secondary objectives are statistically dependent, the formulation of attitude towards uncertainties becomes complicated.

2.4.4 Triggering the need for decision

In operations, not making a decision is a decision itself. However, most of the decision tasks are triggered by *events*. Such events can be divided into the following categories:

---

[2] Rationality here means simply avoidance of circular preferences, such as "A is better than B, B is better than C, C is better than A", see Figure 2.3.

1) event of new measurement data becoming available
2) foreseeable external events
3) unforeseeable[3] external events
4) foreseeable internal events
5) unforeseeable internal events.

When *new measurement data becomes available*, information about system state is updated. With the new updated information the predictions about consequences of potential actions are with less uncertainty. Thus decisions should be revised always when new measurement data becomes available. Selecting automatically control actions are decision tasks invoked always when data becomes available. With standard control theory it is assumed that new data arrives at regular intervals, called the sampling interval, but the theory can be readily extended to irregular sampling as well. Control theory – in particular Model-Predictive Control (MPC) – also deals with uncertainties through system noise models, and thus falls within the SDT. Usually the attitude towards uncertainties in control is neutral, as the uncertainties related to different actions are quite similar.

Production schedule allocated to a production line, planned availability of some raw materials, and changes in utility – e.g. electricity or water – cost are examples of *foreseeable external events*. An event being foreseeable means that the decision tasks should be triggered well in advance to the occurrence of the event so that preparatory decisions and corresponding actions can be made before the event. Setting up the trigger within ODSS is a rather straight forward task once it has been realized that such an event may occur in the first place. The lead time before the event may be chosen at the design phase of ODSS for the task based on production system knowledge.

Incorporating an urgent customer delivery into a pre-existing production schedule, unexpected change in utility cost, or finding a raw material batch to be out of specifications are examples of *unforeseeable external events*. As with all unforeseeable events, triggering by them is based on *event detectors*, i.e. data analyzer functions. As the set of potential external unforeseeable events tends to be more limited in scope and as the information available about external actions on the operations is less versatile than internal information, event detectors for unforeseeable external events tend to be easier to set than those for internal ones.

Grade change, planned maintenance and change in portions of raw materials are examples of *foreseeable internal triggers*. As they are internal ones, they typically arise when other operational decision tasks are completed. Hence triggering by internal foreseeable events is *a mechanism to coordinate operational actions*. A mechanism of coordination is that two

[3] "Unforeseeable" is here to be understood as "not known with certainty in advance" instead of "completely unknown before occurrence". As the discussion below shows, ODSS will attempt to generate prewarnings of unforeseeable events which is possible only if there may be some evidence about an upcoming event prior to its actual occurrence.

decision tasks are joined to a single decision making process, so that one task simply generates at completion an event that triggers the second task. Obviously, the coordinated approach has less degrees of freedom for decisions, but may be more tractable. Operational and quality upsets and equipment failures are examples of *unforeseeable internal events*. Such events are quite obvious when they occur, e.g. as the production is interrupted. However, the costs of such events are typically very high and hence generating a *prewarning* as a decision trigger is more essential than detecting the event itself. Within the research and techniques of system diagnostics, there exists a huge amount of detection methods, such as those within *Statistical Process Control* (SPC) and its many variants, or *state data clustering*. The modern methods for prewarning generation are discussed in Chapter 5. Common to all prewarning detectors is that they provide probabilistic information; typically the probability that the system is not behaving "under normal operating conditions". Because of the probabilistic nature of prewarning events there is an intermediate decision on whether the evidence about an upcoming unforeseeable event is strong enough so that a decision process about counteractions is to be triggered, or if additional information is to be acquired. When considering evidence about an upcoming unforeseeable event, the goal is to maximize operational performance. As in the large scale industrial operations the cost of not taking counteractions and the event occurring tend to be orders of magnitude larger than that of taking the counteractions in vain, the decision making process about counteractions should usually be triggered already with rather incomplete and uncertain evidence.

2.4.5 Decision about more information before deciding about operational action

There is a huge amount of data – and hence information – about system state, and the online and laboratory measurement systems feed new information with essentially no operational cost. However, there are also information sources beyond the regular data generation and collection that may be invoked on the need basis. Hence within a decision making process about actions on the operations, there may arise decision subtasks about whether to acquire further information before making the decision about the action. Furthermore, there may be several alternative information sources to choose between. Prewarnings about unforeseeable internal events typically have such decision subtasks about acquiring further information.

In operational decision making the sub-decision about additional information considers the quality of decision and the resulting action, and the cost of acquiring the information. The cost can be divided into two elements: direct cost and loss of time. With all elements – direct cost, loss of time and prior information about measurement result – available, this decision task can be formulated as an optimization problem, known also as the optimal measurement problem. However, in practice fully structuring such optimization formulation has proved to be a very demanding task. The ODSS may assist the decision maker in formulating such a problem, but the time taken for the formulation may turn out to be an issue in itself.

2.5 On normative implementation of operations’ decision support systems

The main claims based on the normative analysis about operations decision support systems are that

1) operations is managing a portfolio of decision/action tasks
2) all decision tasks have the same abstract structure derived from formal decision theory
3) uncertainty being an essential component of decision making must be included explicitly.

From the point of view of specification and implementation of operations decision support systems this means that

1) there is a subset of user requirements, referred to as generic user requirements or GURs, which define specifying, populating and analyzing the elements of decision theory
2) a natural choice of data structure is a collection of structures that corresponds to the mathematical structure of decision theory, referred to as SDT structure
3) a subset of generic functionalities – based on methods discussed in Chapter 5 – analyzes completely and incompletely populated SDT structures, and provides automated actions, suggestions for actions, information for making actions and explanations of suggested actions or information.

A version of such generic user requirements is given as Appendix A.

A complete set of user requirements and functionalities include specifications on how results are presented to the users, detailed specification of user-to-user communication, and mapping decision tasks to organizational roles.

We claim the strength of this approach to be:

1) The SDT structure provides a rational and transparent basis for decision making separating "facts" (measurement and response models) from "preferences" (objectives and constraints). When the SDT structure is incomplete, the structure clarifies missing elements and guides the user to seek information for improving decision making. Such information may be obtained not only from data but by explicating tacit knowledge within the organization.
2) Because of the portfolio approach, including new decision tasks is straight forward.
3) Because of the portfolio approach, redistributing decision tasks during organizational changes requires only small changes within the system.

The critical points of normative approach are the following:

1) SDT structure does not safeguard against thought errors, such as false measurement or response models, or incorrect interpretation of strategic objectives to optimization objectives and constraints. As the normative approach relies more heavily on models than present ODSSs, thought errors actually are an increased risk that must be carefully taken into account during the implementation process.
2) The SDT structure and explicit uncertainties in particular are rather abstract. Thus both during the implementation and use the requirements on human comprehension are rather high – the more so the less completely an SDT structure has been populated. However, the largest benefit potential is also in systemizing and rationalizing decision making through more structured approach.
3) Uncertainty as a piece of metadata is structurally complex and has not been made explicit either in current decision support systems or in production history databases. Therefore including uncertainty may require considerable and costly changes also in systems other than ODSS. Due to the complexity of uncertainty, its description must be crude with only approximations. Finding approximations that balance the cost of implementation and the usefulness of metadata will be a challenge in practical systems.

On the basis of research presented in this chapter, normative operations decision portfolio systems are ready for implementation. Small scale studies within this research activity confirm both the opportunities and the challenges.

3. Computational methods and techniques

By Kauko Leiviskä, University of Oulu
Sirkka-Liisa Jämsä-Jounela and Jari Olli, Helsinki University of Technology
Sami Äyrämö, University of Jyväskylä

3.1 Introduction

The amount of collected data in modern process automation environments has been growing explosively during the last decades. Not only the number of collected observations has been increasing enormously, but also the number of different ways to measure various processes and products has grown due to the large number of different sensors and measurement equipment available for process control systems. On the other hand, all the information is not available in the form of measurements of physical or chemical quantities, but there are also vast amounts of information in electronics diaries, document databases, image databases, and so on. Such a flood of heterogeneous digital data may rather overwhelm or even mislead rather than assist its user. As a consequence, collected data stores may remain useless.

In order to efficiently utilize these information sources, to learn from the past, requires advanced data-based methods, knowledge mining tools and processes. As our capability to measure and record facts grows, many old-fashioned data analysis techniques come up against the so-called "curse of dimensionality". Traditional data analysis tools cannot cope with the existing large multidimensional data sets. Moreover, due to the high number of dimensions, it is no longer enough to explore the data sets using trends of individual measurements. The most interesting behaviour can be observed by analyzing the mutual behaviour of all the process variables. Understanding the underlying behaviour of processes in the multidimensional space enables us to deduce and predict future events. The real-world data sets are, unfortunately, often erroneous and incomplete. This means that the classical assumptions about data and parameter distributions (e.g., normal distribution) are often invalid. Incompleteness means that all data values are seldom available in the data set. This means that the use of classical data analysis techniques may even be misleading rather than supportive for decision makers.

The utilization of large-scale data mining/analysis tools is a part of a broader process. Figure 3.1 presents a two-level process model that shares domain-specific and technical responsibilities into separated but nested processes. The goal is that through intensive collaboration between domain and data mining specialists the process ultimately results in automated and reliable application-specific tools that are straightforward and easy to use by decision makers and analysts without expertise in detailed computational and statistical issues. The mining results should be presented using user-friendly and understandable visualization or other representation techniques that are developed as a part of the more technical data mining process. This kind of approach relieves resources from unnecessary technical details for more concrete decision making issues.

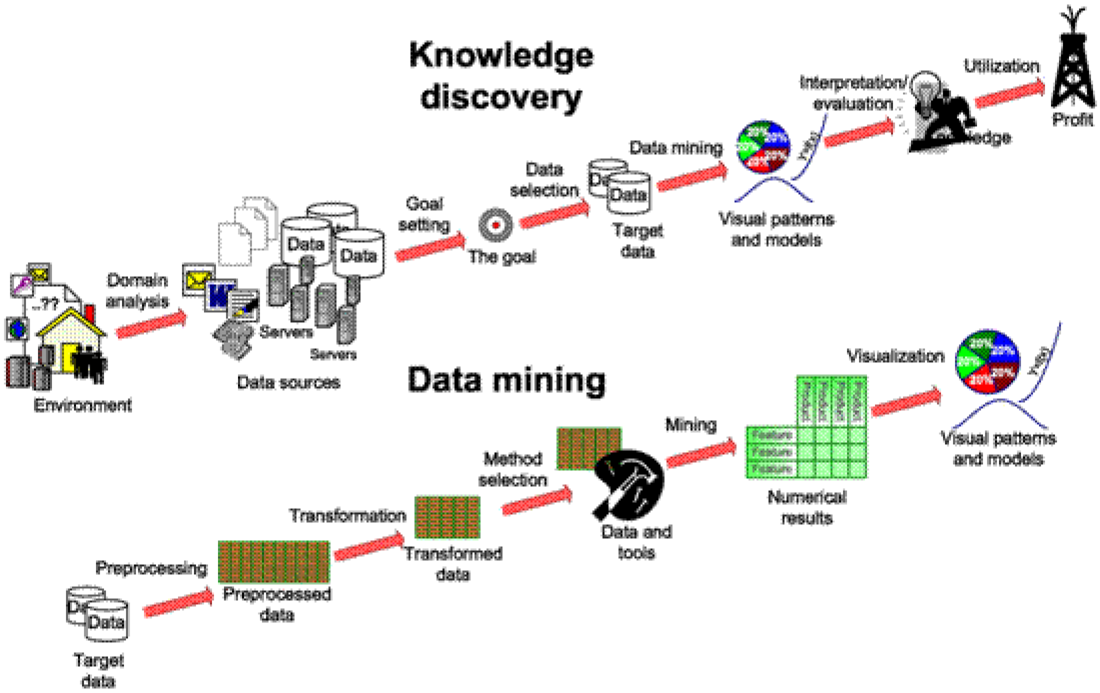


Figure 3.1. Knowledge mining (KM) process model.

The research problem in condensing and combining data includes two points of view: process monitoring or diagnostics. They have, however, some common topics – the first stage is usually the state detection and in both cases it is advantageous to know how this state has been reached. The disturbance situation must be detected, and its source must be identified and eliminated, if possible. The operator must receive the results so that it is still possible to tackle the disturbance and, at least, prevent its effects to other processes.

One difficulty is to compress the excessive data in a suitable form that supports decision making. Several methods are available for the process state detection, monitoring variables describing the process state, feature analysis, and calculation of performance criteria and techniques such as fuzzy logic, clustering methods, case-based reasoning, and self-organizing maps are in use. To get these results into everyday use in process industry requires more research. Several questions still wait for their solution:

- How to upgrade process data so that it is useful for decision making?
- How to detect disturbances, different process states and their changes?
- How to forecast the future behaviour of the process?

- How to handle missing and erroneous data and utilize heterogeneous data?
- Which higher level performance indicators are available?
- How to transfer the process control solutions to other decision making levels?
- How to build transferable, configurable and adaptive systems?
- How to utilize compressed and grouped data and models in optimization?
- What kind of uncertainty is connected to upgraded data and can this upgrading decrease the uncertainty in decision making?

This chapter concerns mainly the first three questions. After presenting general functionalities in Section 3.2, Section 3.3 concerns clustering methods, Section 3.4 the applications of genetic algorithms, Section 3.5 PCA and causal digraphs and, finally, Section 3.6 will end the discussion by introducing measures for maintenance performance.

3.2 General functionalities

The framework for data condensing and combining is applicable for control, diagnostics, production control and optimization of operations. Figure 3.2 shows the case that starts from facts (variables), proceeds via variable grouping and system state evaluation to the actual use in performance monitoring, fault diagnosis and prediction. The same data comes up at different levels of aggregation and it must be consistent at each level. The figure refers to the modular systems presentation and especially in plug-and-play applications the transferability, configurability and on-line adaptation are important issues.

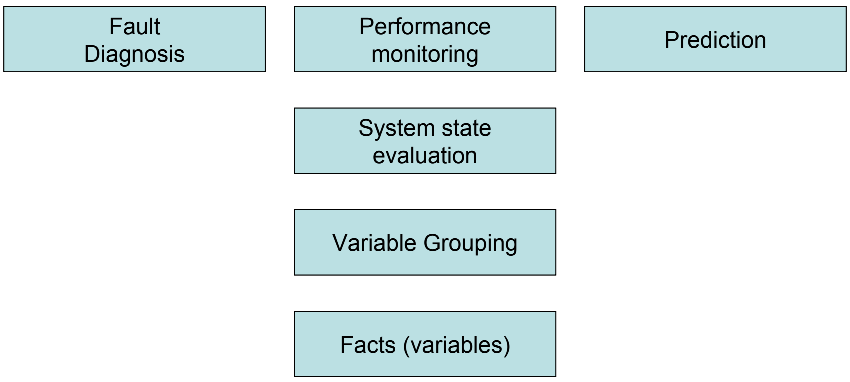


Figure 3.2. An example of combining and condensing data.

Facts (or variables) are the starting point for data processing. They consist of collected process data, information from process operation, indirect measurements, image information, etc. Non-homogeneity is one specific feature, and uncertainty is another. They both call for advanced methods, and so does the increasing amount of data, varying frequencies and different users and uses of data.

Variable Selection and Grouping

Variable grouping takes place automatically or guided by the operators. It starts from the measurements (facts), and the essential variables for the required action are chosen. Selection of the correct data set(s) for modelling is another viewpoint. It includes data pre-processing, outlier detection and so on. In both cases, the evaluation of grouping performance and concretely describing the goodness of the result for solving the original problem is necessary. Measurement uncertainty must be evaluated. Initially, the data (or knowledge) base is collected automatically or by human interviews. As the result, the ordered data (or knowledge) base is ready for the modelling. Depending on the methods, this base can be divided to training, testing and validation data. At the operational level, there are several groups of methods available (Ahola et al. 2007): statistical methods, clustering (see Section 3.3), Bayesian methods, and neural networks together with several hybrid approaches (fuzzy logic with case-based reasoning) (Ahola and Leiviskä 2005). Applications vary from diagnostics and maintenance (knowledge-based systems) to production planning (combining data and knowledge from several sources, guiding systems) and management (textual queries, associative grouping).

State detection

The state detection is mostly an automatic operation. It consists of developing the models based on the grouped data that both form the basis for deciding the process state. It includes also the evaluation of the reliability of models and detection results. It starts from data set(s) after the grouping function and results in process state together with its reliability value. Methods vary from analytical to statistical models including soft sensors and smart analyzers to intelligent methods, e.g. fuzzy logic (Sorsa and Leiviskä 2007). Different factors come up in different applications: diagnostics and maintenance (strict and soft constraints, rule-based systems, model-based diagnostics), and production planning (methods for evaluation of the status of production, products and single orders; status of production machines; predictions and management (scenarios, predictions).

Monitoring

Monitoring is mostly an automatic function, and it is guiding the operator. It reports on the state of the process, compares the state of the process to the target state and reports on deviations. Alarms for exceptional situations and faulty operation of machines, processes and products are included, together with the guidance for recovery.

Several methods are in use. Operation support makes use of visualizing methods, models, short/long-term predictions, and automatic correction in the case of control. Diagnostics and maintenance rely on visualizing, knowledge-based methods for fault location and guidance for recovery. Production planning requires performance measures and schedule follow-up, as do maintenance operations (see Section 3.6). Finally, management can take advantage of market analysis, customer and competitor reviews, and product analysis.

Fault diagnosis

Fault diagnosis can be either an automatic or a manual supporting function consisting of fault detection, fault localization (isolation) and fault recovery. It starts from the information from state detection and the targets set for the operation (e.g. from upper control levels), defining the necessary actions or operation program that guarantees the best possible performance under the constrained situation. The risk connected to the decision should also be evaluated. A lot of methods are in use, and two examples are in Section 3.5.

Prediction

Prediction starts from models describing the process behaviour under normal or exceptional conditions. The results have use in control actions or in monitoring. The confidence in resulting predictions should be included. Once again, a lot of methods are available, starting from simple simulations to the more complicated evaluation of disturbance situations.

3.3 Clustering methods

3.3.1 Data clustering

Clustering is an unsupervised and descriptive data analysis technique, which is widely used, for example, in the field of data mining and knowledge discovery. When considered simplistically, the idea of data clustering is the following: for a set of p-dimensional data points (vectors), a clustering method tries to find a partition in which data points close (similar) to each other are assigned into the same clusters and distant (dissimilar) data points into separate clusters. Each cluster is usually represented by one representative point, prototype, that is some multivariate location estimation (the sample mean, median etc.).

Unsupervised data analysis technique means that contrary to data classification tasks no prior information about cluster structure (objects class memberships) is available for a given data set. Descriptive technique means that it provides novel information about the unknown clusters (groupings) of similar objects. In this way, the hidden structure of an interesting (often multidimensional) data set can be revealed.

Clustering a high-dimensional data set is, in many ways, a challenging task, which may require a lot of intervention by the analysts. If considered strictly from the point-of-view of numerical computation, data clustering is only a non-convex global optimization problem. However, the significance of different clustering solutions cannot be evaluated only with respect to numerical values, but also a philosophical point-of-view is required. For example, making a decision on the correct number of clusters for a given data is an ambiguous task, since one analyst may see the data in a different way than another. Other challenges that are inevitably encountered with data clustering are the computational complexity of clustering problems, the sensitivity of methods and algorithms to erroneous and incomplete data, and the non-uniqueness of solutions. An exhaustive search that goes through all possible partitions is also an impractical approach, since the number of different partitions is very large even for small data sets.

Clustering methods fall roughly into two categories, namely partitioning and hierarchical methods. Other approaches, such as density-based methods (e.g., DBSCAN), fall somewhere in between the major ones. Partitioning-based methods, such as K-means or K-spatial medians, tend to have lower memory consumption than hierarchical methods, which is a considerable advantage in the case of large-scale clustering problems. Because most clustering methods are local-search methods the globally optimal clustering will not be always attained.

3.3.2 Robust data clustering

K-spatial medians is a robust and reliable clustering method, which is based on a statistically robust estimation of prototypes and the K-means-wise expectation-maximization (EM) strategy. Robust clustering techniques are needed, because real-world data sets do not always satisfy the common assumptions about the normal distribution, but they contain noise and gross errors that are more inherent to heavy-tailed distributions. Moreover, missing data may produce unexpected bias to the results. These defects in data sets distort or even break down the classical least squares error-based estimates (for example, Gaussian mixture models, K-means clustering etc.).

The robust estimation of prototypes can be realized in many ways. Perhaps the simplest method is to compute the sample mean by cutting off the most outlying observations from the data sample. However, outlying and extreme values can often be the most interesting observations that should not be lost during the data processing. On the other hand, determining the outlying points can be troublesome in high dimensions. Another option is to compute the coordinate-wise median for each dimension of data set. The problem with this approach is that the estimate ignores the multivariate properties of the data sets, since the coordinate-wise median is based on the univariate orders (the middle value of a set of numbers).

A robust and inherently multivariate clustering method can be obtained by choosing the spatial median for the prototype estimation. For instance, in the case of K-means-clustering this necessitates that the sample mean prototype estimator is replaced by the spatial median estimate. When compared to the other traditional methods, such as K-means or Gaussian mixture models, K-spatial medians are more insensitive to extreme errors and missing values. Robustness against extremely deviating values is essential in the context of clustering large-scale process data, since outlying values and errors are impossible to recognize and trim due to the high number of dimensions. Using the spatial median as the most representative point for a set of observations, one can recognize both the main bulk of data (usually representing the expected behaviour) and extreme observations (often representing problems and errors in the process).

Although the K-spatial median clustering problem tolerates erroneous and outlying values and can be solved using a similar expectation-maximization strategy as K-means, the difficult point is the fast, accurate and reliable computation of the spatial median point (aka Fermat-Weber point) in the presence of missing values. For this purpose, the SOR (successive-over-relaxation)-accelerated iterative Weiszfeld algorithm has been developed to approximate the spatial median estimate. The SOR-method has shown to be accurate and fast enough for the scale of process industry applications. When considered from the cluster analysis point of view, a typical assumption is that the use of robust estimates is not cost efficient due to the increased computational cost and the uncertainty of the results. However, this assumption is not necessarily valid. Using the fast and computationally reliable SOR-accelerated method for approximating the spatial median estimates and an efficient method for initializing their values, one can reduce the number of overall clustering iterations and thereby win back the cost of robust estimates. In order to ease the burden of validating different models, robust clustering validation techniques, such as robust silhouettes and R&D can be employed in estimating the correct number of clusters. Due to the underlying robust statistics, these indices produce reliable information about clustering validity in the presence noise and outliers.

3.3.3 Clustering applications in process industry

High-dimensional process data set many challenges from the analysis and decision making point-of-view. In Figure 3.3 one can see a low-resolution sample of a real-world history data set from an industrial process, which is transformed into the form of a (N x p) data matrix. Each row of the matrix represents one trial point of a process. Each of the N trial points consists of p variables measured from the process. It is clearly visible that there are a huge number of observations and dimensions. There exists also a lot of missing values. The challenge lies in processing the data into more understandable form. While the data is impossibly large for manual pre-processing and analysis, data clustering provides two choices for extracting information from such huge data sets.

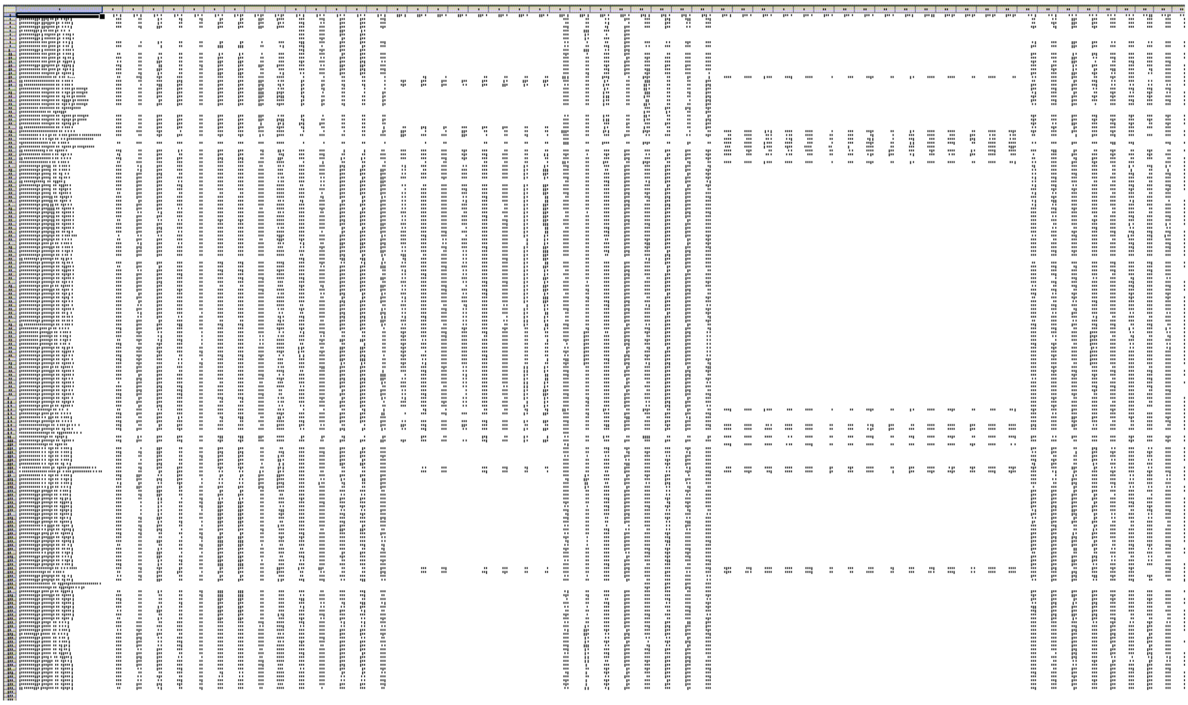


Figure 3.3. A real-world process data set.

The first approach is based on the classical clustering principle where groups of similar observations are assigned into groups based on an appropriate (dis)-similarity measure. Each group should then represent a collection of trial points in which the process has been in the same state. By visualizing the obtained clusters, one can make further analysis and evaluations about the process history. The principal component analysis (PCA) is a projection technique by which one can transform high-dimensional data into a low dimensional space. Figure 3.4 shows an example of a projected high-dimensional process data set. Diamonds depict the four cluster prototypes. Data points are assigned into clusters by colours. From such visualizations, one can observe the compactness of cluster structures and outlying cluster members. Low cluster cohesion indicates that process is not stable. On the other hand, outlying points within a cluster indicate probably more serious problems. The number of clusters suggests the number of different states the process has been running.

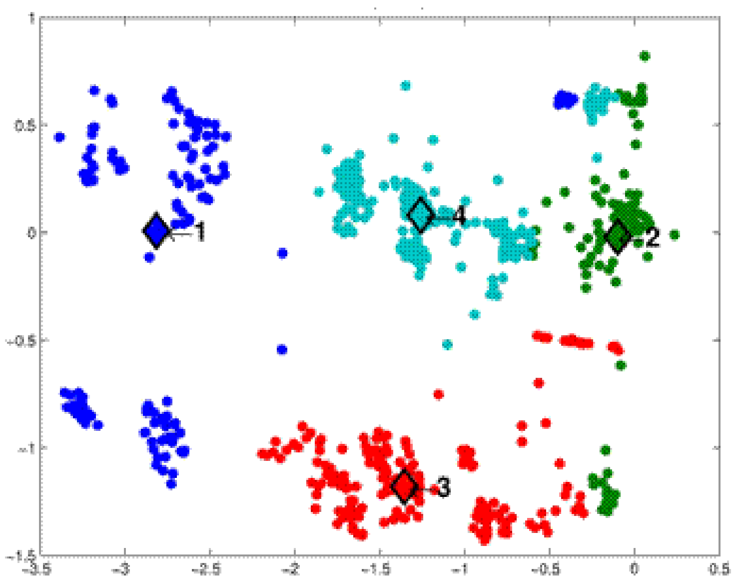


Figure 3.4. Two-dimensional PCA-plot on four data clusters.

While Figure 3.4 reveals the structural distances and relationships of the clusters, Figure 3.5 shows the occurrence of the clusters in a temporal order. The cluster prototypes are mapped to their closest points and plotted above the figure. These points represent the most typical condition for each state. Using this illustration one can learn about the order of the different states. For instance, the states usually occurring prior to serious problems provide valuable information for predicting and avoiding the coming problems. Techniques for association rule analysis can be used to find the most interesting sequences.

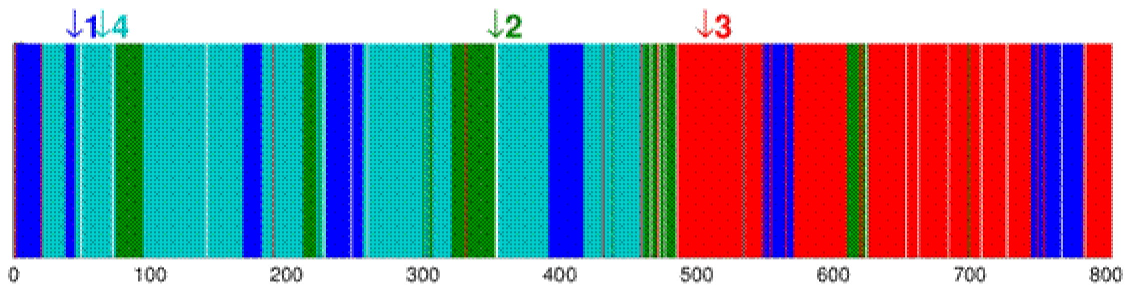


Figure 3.5. Temporal view of the clusters.

Variable ranking with respect to a clustering result provides valuable information about the contribution of different variables to clustering. Figure 3.6 shows an example of a variable, which contributes significantly to the clustering. The background histogram shows the overall distribution for the variable, while red and green histograms present the distribution of cluster number one and two, respectively. Black straight lines denote the cluster prototypes. The utility of this ranking and visualization lies in the possibility to find quickly the variables that are contributing mostly to the formation of different states. For example, the PCA technique finds the directions of the largest variation in the data, but does not provide any information about groupings. Hence, clustering with variables ranking and visualization provides much more intelligent knowledge about process than different variance analysis techniques.

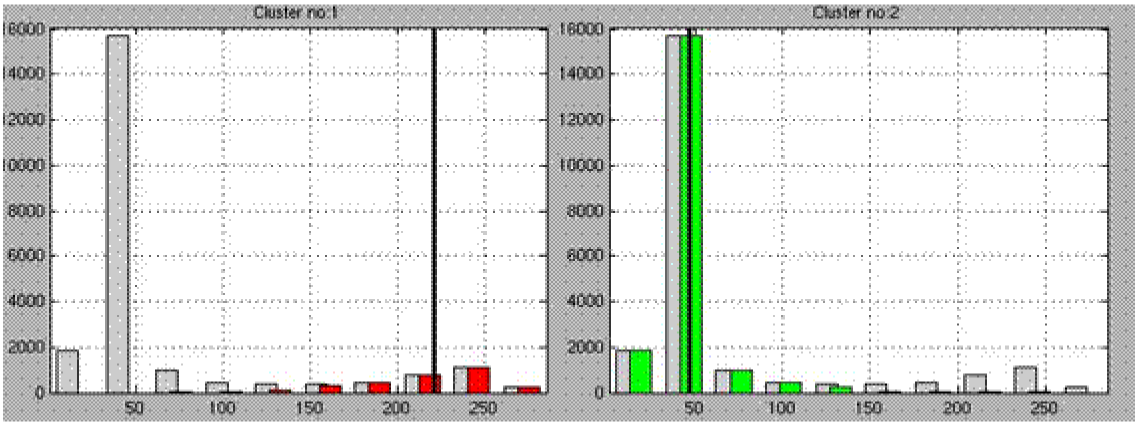


Figure 3.6. Cluster-wise distribution of a variable.

Another approach of using data clustering for analysis of large history data sets utilizes principles of time-series analysis. Actually, after transposing and normalizing a given data set, one can use clustering methods for the grouping of variables, i.e. extracting similarly behaving variables. In this way, the analyst can select the most representative variable from each group. Differences in variables within a group predict the values of other variables.

Utilization of all the aforementioned clustering approaches with visual interpretations requires scalable, robust, and automated tools. Relying on the classical assumptions about normal distributions, data trimming and imputation techniques, and sensitive least-squares error estimates are too sensitive for the current erroneous and incomplete data sets. The methods and algorithms used for building cluster models and visual illustrations should be as free as possible from strict statistical assumptions and input parameters, since this reduces the load from the analysts and decision makers to determine the correct settings for the tools.

3.4 Applications of genetic algorithms in modelling and diagnostics

Genetic algorithms (GA) are optimization methods mimicking evolution. Optimization bases on the development of the population comprising a certain number of chromosomes. The development of the population uses two tools characteristic to evolution: crossover and mutation. Each chromosome codes a possible solution to the optimization problem. Binary or real valued coding are in use. In binary coding, each variable requires a suitable number of bits to guarantee an accurate enough solution. The link between the population and the optimization problem is the objective function.

Time delay is the property of a physical system where the change in the input variable shows a delayed response. If material or energy is physically transported in a process or plant there is always a time delay associated with the movement. Time delay is also referred to as dead time, transportation lag or distance-velocity lag. In addition to the pure time delay, apparent time delays may result due to measurement processes or when a lower order model approximates a higher order process. Distributed delays are typical for the flow processes where the change in the response follows a certain distribution instead of an abrupt change.

Various techniques for time delay estimation have been proposed and implemented. A major difficulty with most of the available approaches is that the methods are applicable to time delay estimation for the SISO case, only, and their extension to the multivariable case is not straightforward. However, in data mining and process analysis, often multivariate data is met and the time delay needs to be developed for several variables and groups of variables. It is necessary to develop methods for estimation of time delay for multiple inputs and/or disturbances. This becomes difficult especially when working with normal process data with no specific test signals. Then, in some cases with on-line data, the correlation rates can be weak and only experts can define the final delays before the actual use in modelling.

The delay estimation scheme presented here combines genetic algorithms and PCA. Genetic algorithms produce optimal delays with objective functions based on PCA. This study used binary valued coding of chromosomes. Reliable results require repeated optimizations, as does the estimation of the validity of the results. Each optimization consists of 20–30 new generations.

The goodness of the chromosomes is evaluated with the objective functions based on PCA. The data is delayed according to the decoded information obtained from each chromosome. The delayed data results from moving the variable columns in relation to each other as depicted in Figure 3.7 shows the principle of generating new generations, where the delays between variables vary. Note! Variables are in columns and time runs from the top to the bottom. The figure shows three generations. The optimization maximizes the variance explained by a certain number of principal components.

a_{11}	a_{12}	a_{13}
a_{21}	a_{22}	a_{23}
a_{31}	a_{32}	a_{33}
a_{41}	a_{42}	a_{43}

a_{11}		
a_{21}	a_{12}	
a_{31}	a_{22}	a_{13}
a_{41}	a_{32}	a_{23}
	a_{42}	a_{33}
		a_{43}

a_{11}		
a_{21}	a_{12}	
a_{31}	a_{22}	
a_{41}	a_{32}	a_{13}
	a_{42}	a_{23}
		a_{33}
		a_{43}

Figure 3.7. Moving variables in relation to each other.

The approach was tested using data from the paper machine simulator, developed in Helsinki University of Technology, in the Laboratory of Process Control and Automation. The data included over 50 variables and the variables had to be grouped based on the cross-correlation and graphical analysis on mutual correlations into five groups.

Because the causal relations between the variables were unclear, no prior knowledge about output variables was available. This means that the delayed data had no reference time instants. The results of the time delay estimation for one of the five groups are in Figure 3.8.

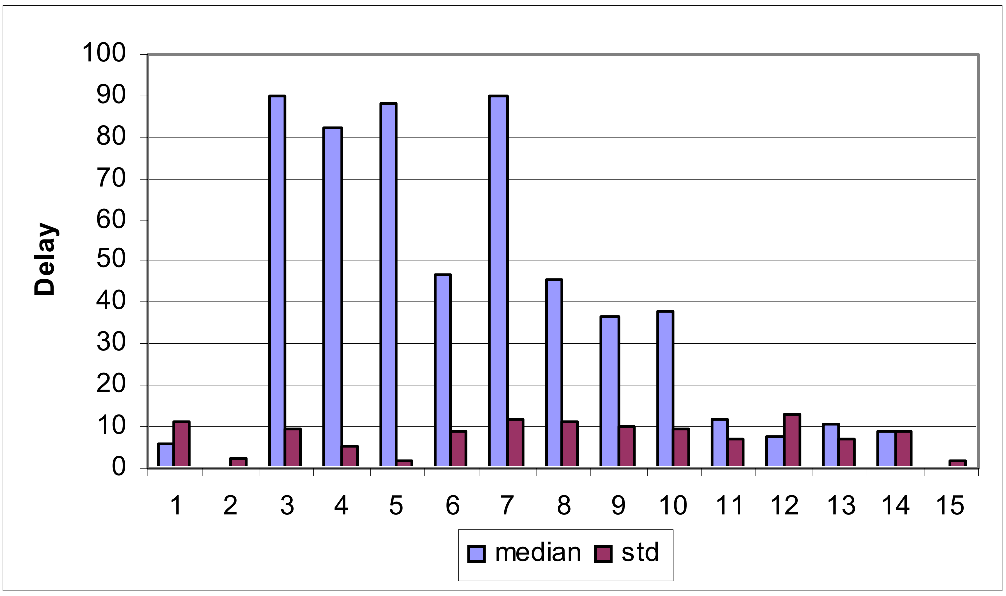


Figure 3.8. The results of time delay estimation for one group of 15 variables.

Next, estimating the time delays between the groups follows. Over 90 percent of the variation in each group was captured by the first principal components. Thus, the first PCs represented the groups. Time delays between the groups were estimated using the similar procedure as for separate variables. The results of the time delay estimation between the five groups are in Figure 3.9. There was no delay between groups 2, 3 and 5, but groups 1 and 4 had considerable delays compared with the others.

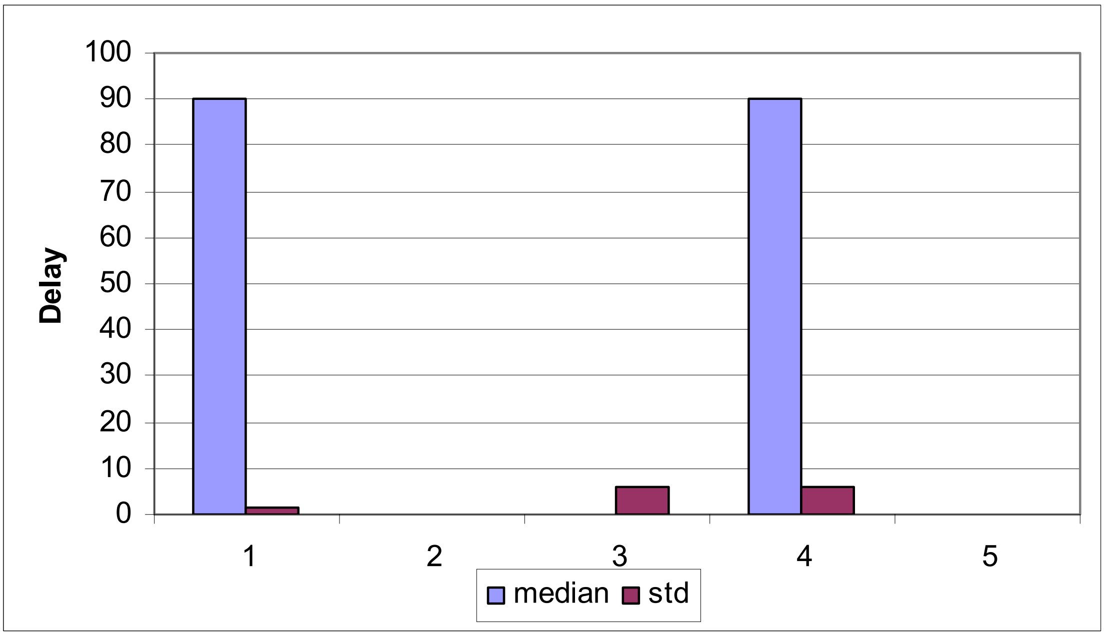


Figure 3.9. Time delay estimation between five groups.

Genetic algorithms using real-valued coding apply also for parameter identification of Haldane kinetics in the Chemostat model for wastewater treatment given in following equation (Sorsa and Leiviskä 2006):

$$\mu(c_s) = \frac{\mu_0 c_s}{K_S^{-1} c_s^2 + c_s + K_I}.$$

The values used in simulations are presented in Table 3.1.

Table 3.1. The parameter values for the Haldane kinetics equation.

μ_0	K_S	K_I
0.74	15	9.28

Prior to the identification of the model parameters, several optimizations were run to obtain optimal parameters for the genetic algorithms. A typical evolution of the fitness value is in Figure 3.10. Initially, the population undergoes a fast evolution towards optimum followed by a more gentle decrease in the mean of the fitness values.

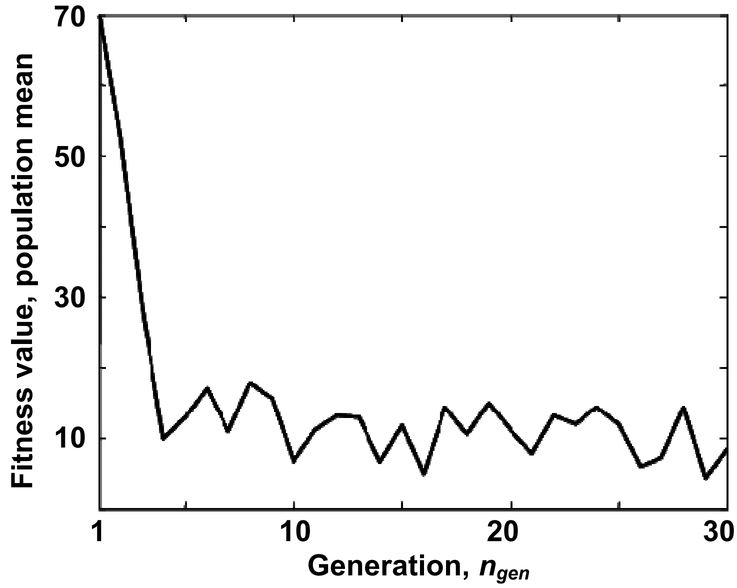


Figure 3.10. Typical evolution of the fitness value.

The initial population was taken randomly from the uniform distribution. The model identification procedure with genetic algorithms was repeated with 200 different initial populations to guarantee the validity of the results. The overall algorithm is as follows:

1) Create a random initial population with n_{pop} chromosomes.
2) Evaluate the fitness of the chromosomes through the objective function. Apply elitism.
3) If n_{gen} generations are reached, go to step 5.
4) Apply reproduction and mutation and go back to step 2.
5) Obtain the results.

The best set of model parameters was obtained from the 200 optimizations and is presented in Table 3.2.

Table 3.2. The best set of model parameters for one operating area.

μ_0	K_S	K_I	RMSE
0.88	10.64	11.51	0.26

The best parameter set was the one giving the lowest RMS value of the prediction error. Comparing Tables 3.1 and 3.2 shows that obtained parameters are not equal to the actual ones. Figure 3.11 presents the actual and the predicted substrate concentrations for both step responses (up and down). The figure shows that even though the obtained parameters are not the same as presented in Table 3.2, the prediction accuracy is good. This is due to the fact that the data used to identify the model was limited only to low substrate concentrations. The other operation point showed similar behaviour.

Results show that genetic algorithms can be applied successfully to parameter identification of the nonlinear models at least when the model structure is known. However, the selection of the proper model structure is sometimes the more difficult task than the parameter identification. The benefit of genetic algorithms is that also model structure selection can be included into the objective function. However, it would add a discrete variable to the problem which may cause some problems for optimization.

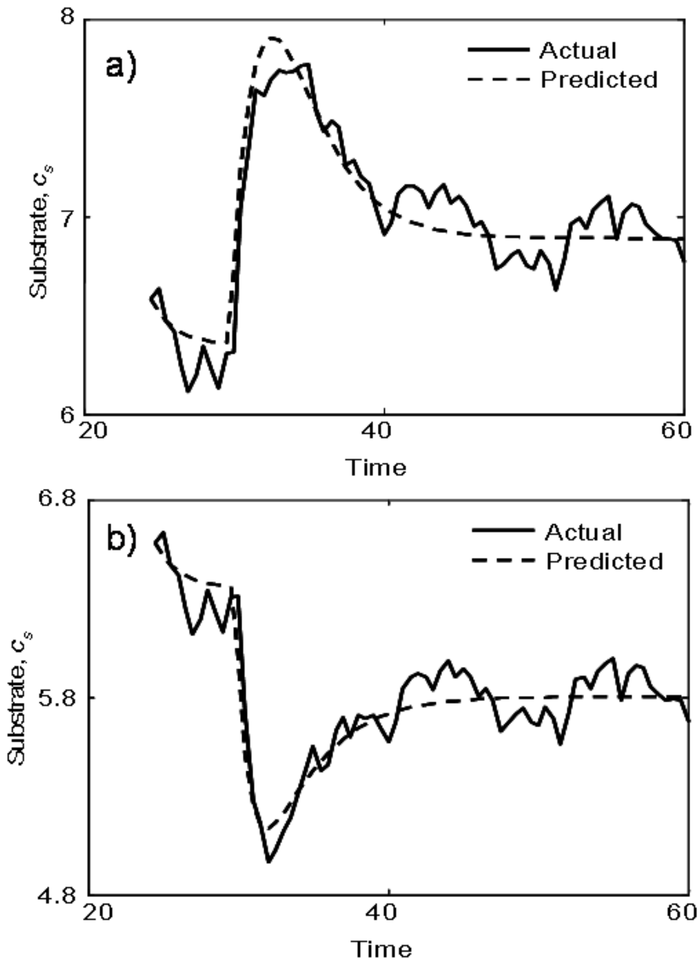


Figure 3.11. The actual and the predicted outputs of the system for the one operating point: a) the positive step change and b) the negative step change. The predicted output follows the actual output accurately.

Genetic algorithms have some advantages in sensor and variable selection for the diagnostics systems. The following results come from the test rig used in earlier studies. It consists of an engine and a transmission between two axes on roller bearings. Seven accelerometers located at different places on the axis are measuring two axial and five radial vibrations. The primary function of the rig is to simulate different fault modes that arise when defective elements are added to the rig. This way it is possible to collect data for several independent fault modes (rotor imbalance, three different coupling misalignments between the engine and the input shaft, bent shaft, and three different bearings faults). The test rig is therefore able to generate data that enables the creation of a separate model for each fault type. As a result, the diagnosis system is able to specify with a certain probability which failures are more likely to occur according to a given data set.

For each fault mode as well as for normal conditions, the measurement set includes a hundred accelerometer measurements at five different rotation speeds (15, 16, 17, 18, 19 rpm). In addition to the rotation speed, five others features are calculated from accelerometer measurements and used as variables. Root-mean-square, a(rms), and kurtosis are obtained from acceleration signals. The average of the three highest values of the jerk signal denotes the jerk peak. Root-mean-square velocities are calculated in two different frequency ranges, 10–1000 Hz and 20–85 Hz, and the resulting features are marked V1 and V2, respectively. This means that the data set includes 35 variables at each rotation speed.

In this system, the variable selection using GA occurs in two successive steps. This enables a better control of the variables implicated and assures reproducibility of the algorithm results during its tuning. The first GA selects the best of sensors, and then the second one chooses the best set of variables within those sensors. The aim is to reduce first the amount of sensors from seven to a maximum of three and the number of associated variables from 36 to ten, at most. If only one sensor remains, then all associated variables are chosen. Otherwise, the second algorithm selects the relevant variables among the remaining sensors.

Table 3.3 shows an example of results. Each fault type is connected to the number of the chosen target variable. The first genetic algorithm chooses one or several sensors associated with this target variable. Finally, the second genetic algorithm chooses the list of relevant variables from these selected sensors.

All the sensors are in use, either through a direct measurement or through one of the derived features. For each fault type, models are generated using two to ten variables belonging to one to three sensors. This indicates that the variable selection target has been reached as the GA optimization successfully selects relevant variables. However, the fact that all sensors are necessary to perform fault diagnosis suggests the initial problem might be under fitted. In other words, at best the amount and current position of the different sensors is already optimal. Most probably, however, different measurements with different localization could provide a better representation of problems.

Table 3.3. The results of sensor and variable selection.

Cases	Target	Sensors	Variables	No of variables
No fault	30	3, 4, 6	12, 14, 17, 19, 26, 29	7
Imbalance 11 g	15	3, 5, 6	11, 13, 21, 22, 23, 25, 26, 29, 30	10
Imbalance 6.1 g	29	4, 6	19, 30	3
Bent shaft	35	2, 7	7, 10, 31, 34	5
Misalignment 1	35	2, 3, 7	6, 7, 9, 10, 13, 15, 31, 34	9
Misalignment 2	25	1, 4, 5	4, 5, 17	4
Misalignment 3	5	1, 4	20	2
Rolling element	17	1, 4, 5	1, 16, 20, 24	5
Outer race	32	7	34	2
Inner race	29	1, 2, 6	1, 2, 6, 7, 9, 10, 27, 30	9

3.5 PCA and causal digraphs in diagnostics

3.5.1 Introduction

This section describes operative decision making from the standpoint of process diagnosis. Process here stands for a physical process and diagnosis for the identification of the cause of some abnormal phenomenon. The causal digraph (CDG) and variants of Principal Component Analysis (PCA) methods with fault isolation capabilities take care of the diagnostic task. CDG was chosen because it is able to infer the type of the identified faults (process fault/sensor fault) and provide information about the set of possible faulty process components. The CDG method has the added benefit to diagnose previously unknown faults. The PCA methods are a relatively easy way of model building. These latter methods, however, are limited to diagnose a predefined set of actuator and sensor faults. Note that these methods, in contrast to the CDG method, are not able to diagnose process faults.

Fault diagnosis is also a decision making problem. In the following, the fault diagnosis problem is put into the framework of decision making:

1) Define the decision making problem:
   a) Facts: knowledge and available measurements of the process. The knowledge is represented using the causal digraph or PCA model.

b) Constraints: model accuracy and only fault free data in the modelling stage; limited explanation capacity due to lack of physical meaning of the model.

c) Goals: a system that is able to detect and isolate faults.

2) Decision making:

a) Collect data.

b) Test consistency between data and knowledge. Chose one action from the action space {fault, no fault} based on the test result.

c) If the action "fault" was selected in the previous step then a hypothesis set (suspected faults) is generated as a consequence.

d) Every hypothesis in the set is tested against the knowledge and observations.

e) The most likely hypothesis is chosen from the set.

The methods presented here can, with some effort, be implemented into factory information systems. The role of the diagnosis methods of the information system is to provide support to the factory personnel when tracking faults in the process. The role of the end user during the system setup phase is to provide knowledge (e.g. the causal relations) to be included in the system. During the operational phase, the end user utilizes the information and makes decisions regarding maintenance. Another role of the end user is to give feedback about the system's performance.

3.5.2 Isolation-enhanced and partial PCA

While PCA and other multivariate approaches are very effective at detecting faults, one important issue they do not specifically address is the fault isolation. Contribution plots can be used but they can often give spurious results. The idea of Partial PCA (PPCA) is to generate sub-models directly by PCA (Figure 3.12). When data is evaluated against a properly designed partial PCA subspace, the residual will only be sensitive to faults associated with the variables present in the reduced subset of variables.

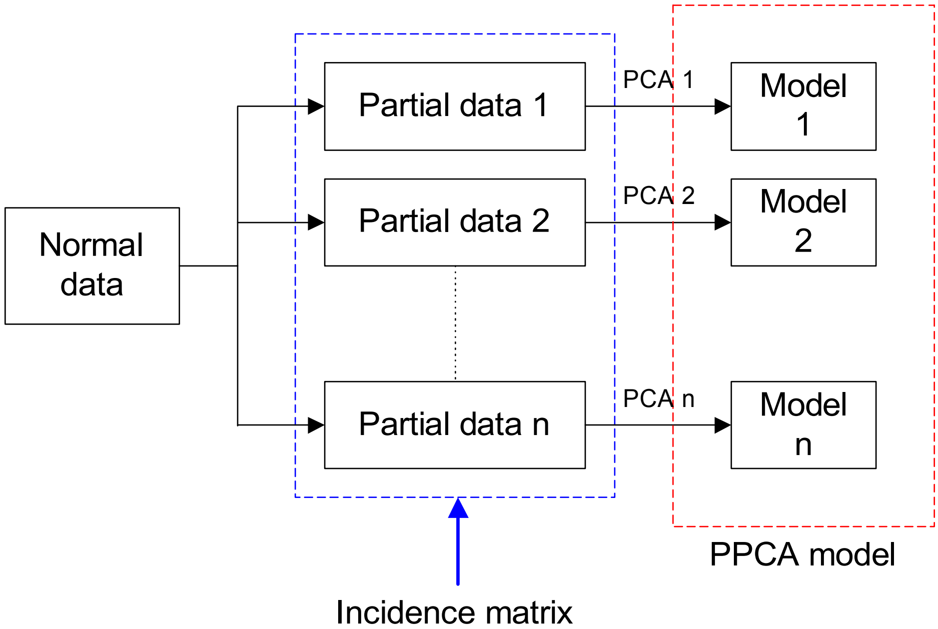


Figure 3.12. Partial PCA scheme.

The primary residuals of the partial PCA model are only sensitive to the faults included in the models. Based on this property, the structured residuals can be obtained from the set of partial PCA models, the variables of which are differently selected according to the designed incidence matrix. An example of an incidence matrix is in Table 3.4.

Table 3.4. A strongly isolating incidence matrix.

	f_{x1}	f_{x2}	f_{x3}	f_{x4}
r_1	1	1	1	0
r_2	1	1	0	1
r_3	1	0	1	1
r_4	0	1	1	1

In the incidence matrix, the rows represent residuals while the columns represent corresponding faults. The number '1' in the matrix means the residual is sensitive to the corresponding fault, while the number '0' refers to the insensitivity of the residual to the fault.

In isolation-enhanced PCA, the fault filter matrices are designed according to each row of the incidence matrix. The primary residuals of the full PCA model are filtered by the designed matrices to form the structured residuals, shown in Figure 3.13.

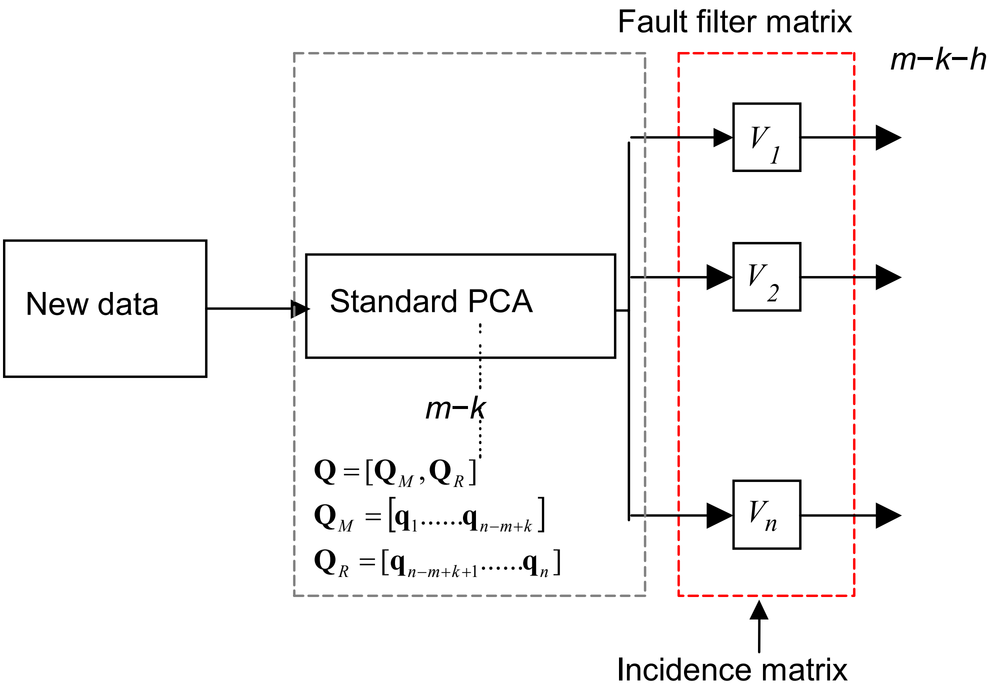


Figure 3.13. Isolation-enhanced PCA scheme.

3.5.3 Improvements

In the partial PCA method, the optimal residual of the ith partial PCA model with respect to the jth fault among all the considered faults, is calculated by linearly combining structured (primary) residuals in the following as

$$r_i^j(t) = \mathbf{s}_i^j \cdot \mathbf{e}_i(t)$$

where $\mathbf{s}_i^j$ is a unitary row vector that needs to be designed so that the fault sensitivity of the residual is optimized. This is a new approach for generating optimal residuals as compared to previous methods in the literature.

Similarly, for the isolation-enhanced PCA method, the optimal residual with respect to the jth fault among all the considered faults is calculated by

$$r_i^j(t) = \mathbf{s}_i^j \boldsymbol{\varepsilon}_i(t) = \mathbf{s}_i^j \mathbf{V}_i \mathbf{e}(t)$$

With these new approaches, more residuals are produced with respect to different faults; hence the incidence matrix is expanded.

In order to form the fault signature, the optimal residuals need to be evaluated by a fault detection algorithm. The bootstrap technique and the double sided CUSUM method of Page and Hinckley, which can detect both positive and negative jumps in the mean of a noisy residual, are combined to fulfil this task. The CUSUM method is able to provide the more robust detection in a noisy environment in comparison to the simple threshold method, even though there is some degree of detection lag. The general design procedure for both the partial PCA method and the isolation-enhanced PCA method is as follows:

1) Pre-process the training data (mean centred and scaled by standard deviation) and perform the full PCA. Determine the number m−k and matrix.
2) Design a proper incidence matrix on the basis of the number m−k and the matrix.
   a) For the partial PCA method, construct a set of partial PCA models on the basis of the incidence matrix. Design the row vector optimizing the fault sensitivity of the residuals from the set of partial PCA models. Modify the incidence matrix on the basis of the optimal residuals.
   b) For the isolation-enhanced PCA method, design the fault filter matrix on the basis of the incidence matrix. Design the row vector optimizing the fault sensitivity of the residuals and modify the incidence matrix accordingly.
3) Generate the fault-free residuals with the training data set for both the partial PCA method and the isolation-enhanced PCA method; apply the bootstrap technique to the fault-free residuals in order to obtain the parameter of the minimal detectable change for the CUSUM method.

3.5.4 Case study: paper machine simulator

This case study on fault detection and isolation was carried out on a paper machine simulator. Next, the simulation environment used is described together with an explanation of the experiment.

For the case, the Advanced Process Simulator (APROS) was used to construct the paper machine model. A general description of the APROS simulator is given on the APROS website. The APROS simulator provides first principle models for the necessary components used in constructing and parameterizing the model for the paper machine. An automation system with 12 control loops was also constructed. The quality variables, basis weight, ash rate and moisture of the paper are controlled in cascade control loops. In the headbox, the stock jet ratio is controlled in the cascade loop by manipulating the setpoint of the inner pressure control loop. In the stock preparation section, the stock consistency in the machine chest is controlled by manipulating the dilution water valve. In the dryer section, the setpoints of the pressures in the steam system are obtained from the moisture control loop.

The case study was limited to the six possible additive sensor or actuator faults in the variables. Both the partial PCA method and the isolation-enhanced PCA method were designed for these six possible faults according to the procedures presented above. The studied faults are in Table 3.5.

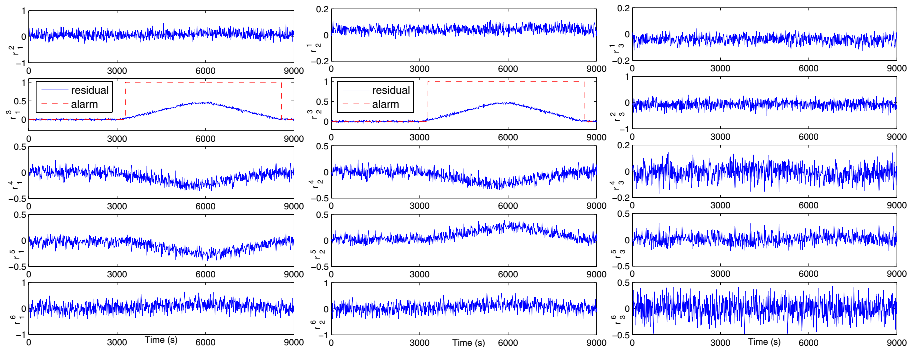
Table 3.5. The studied faults.

Fault no.	**Fault**	**Type**	**Size/Slope**
1	Basis weight actuator fault	Abrupt	Size: 0.03
2	Filler actuator fault	Abrupt	Size: 0.05
3	5th dryer upper valve actuator fault	Incipient	Size: 0.05 Slope: 0.00125/min
4	Moisture sensor fault	Abrupt	Size:0.35%
5	Basis weight sensor fault	Incipient	Size: 2.5g/m^2 Slope: 0.06g/m^2/min
6	Headbox pressure sensor fault	Abrupt	Size: 10kPa

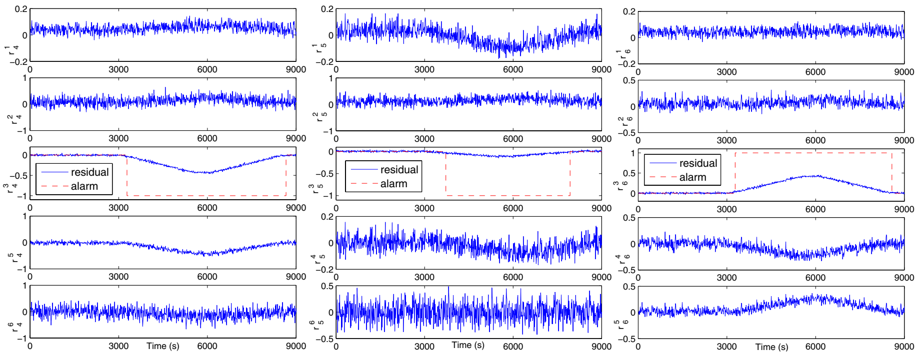
As an example, the fault diagnosis result of fault scenario 3 is in Figure 3.14.

The correct fault was found by comparing the detected structured residuals with the incidence matrix.

For comparison purposes, the results of the classical T2 and SPE contribution plot methods are shown in Figure 3.15 for fault scenario 3. It is clearly visible in Figure 3.15 that the index SPE detects and isolates the 3rd fault (in the 7th variable), while the index T2 fails to perform either the fault detection or the fault isolation.



(a) Residuals r_1 (b) Residuals r_2 (c) Residuals r_3



(d) Residuals r_4 (e) Residuals r_5 (f) Residuals r_6

Figure 3.14. Results for fault scenario 3 with partial PCA.

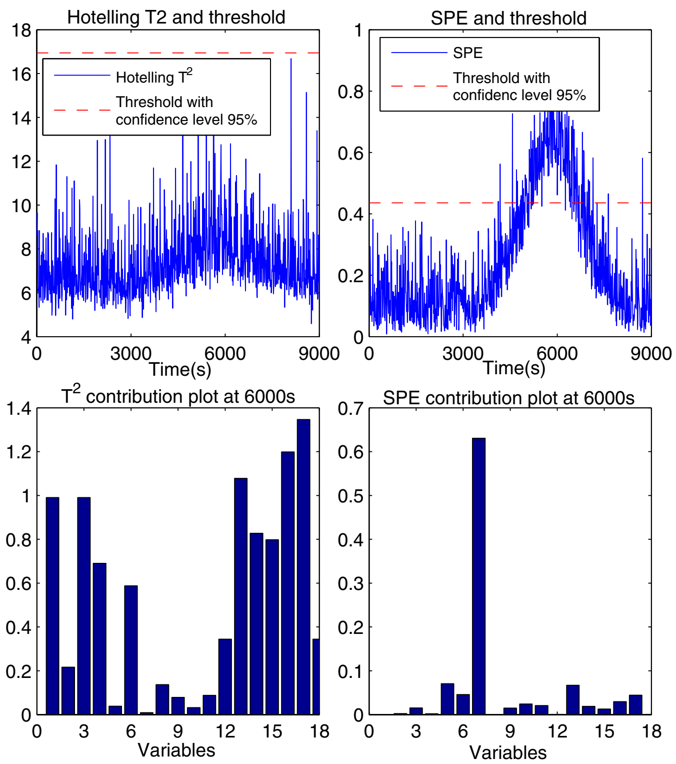


Figure 3.15. Results of the T2 and SPE contribution plot for fault scenario 3.

Comparisons between the partial PCA, isolation-enhanced PCA, classical T^2 and SPE contribution plot methods reveal similarity between the partial PCA method and the isolation-enhanced PCA method. Both methods are able to detect and isolate the faults as designed. Moreover, both of the PCA-based methods provide better fault isolation results than the classical T^2 and SPE contribution plot methods. For easy access, the results of the different methods are in Table 3.6.

Table 3.6. Comparison of the results obtained with different methods for different fault scenarios.

		Partial PCA	**Isolation-enhanced PCA**	***T^2* and contribution plot**	***SPE* and contribution plot**
f_1	Detection	Yes	Yes	No	Yes
	Isolation	Yes	Yes	No	Yes
f_2	Detection	Yes	Yes	No	No
	Isolation	Yes	Yes	No	No
f_3	Detection	Yes	Yes	No	Yes
	Isolation	Yes	Yes	No	Yes
f_4	Detection	Yes	Yes	No	No
	Isolation	Yes	Yes	No	No
f_5	Detection	Yes	Yes	No	Yes
	Isolation	Yes	Yes	No	Yes
f_6	Detection	Yes	Yes	Yes	Yes
	Isolation	Yes	Yes	No	No

3.5.5 Enhanced dynamic causal digraph

This chapter introduces a novel dynamic causal digraph reasoning method for fault diagnosis in a paper machine short circulation process. The novel method improves the detectability and the capacity to handle process faults. The detectability is enhanced by separating different fault effects in the residual generation, and the presentation of the inference mechanism between arcs allows the method to locate the process fault on the arcs.

Firstly, the detection of the global residual may vanish in some cases owing to cancellation of the different fault effects, thus giving an incorrect detection result. Secondly, the method assumes that a change in the variable is the primary fault, which is not true for a process fault. In order to compensate for these problems, a method to separate different fault effects in residual generation is presented. Furthermore, an inference mechanism between arcs has been developed to locate the process fault on the arcs:

1) Generate the global (GR) and local residuals (LR).
2) Detect a possible abnormality in the residual signals using the CUSUM method.
3) Modify the residuals by considering fault effects with different directions and apply the CUSUM method to the modified residuals in order to form the detection set.
4) For the variables in the detection set, locate the primary fault and identify its nature by means of the fault isolation and nature rules.
5) In case of a process fault, an additional inference step between arcs is performed in order to locate the fault on the responsible arc(s).

In order to manage the specific cases when GR and LR become too small to detect due to the cancellation of different fault effects, the fault effects with different directions are taken into account and separated. The proposed approach to perform this is given as follows:

1) Test whether detection of the residual vanishes because of the different faulteffects, go to step 2.
2) Determine the fault effect which is opposite in direction to the residual in question.
3) Generate a new residual by excluding the effect of the fault found in step 2.

The idea behind the proposed inference mechanism is to test the consistency between the sets of suspected arcs formed from fault origins and the knowledge of the output arcs from the same node. This knowledge is introduced into the digraph by a knowledge matrix, and a consistency test is performed by matrix manipulations. Only the sets of suspected arcs which are consistent with the knowledge matrix of the digraph are considered as possible results.

3.5.6 Examples

Three different types of faults have been introduced into the APROS paper machine model in sequence in order to test the proposed method. The first fault is a valve fault in the basis weight actuator. In the APROS model, the fault is introduced by increasing the parameter ‘nominal pressure drop’ of the basis weight valve from 30kPa to 36kPa. In reality, the corresponding fault is a blockage of the basis weight valve due to a fibre flocculation phenomenon, which makes the opening of the valve’s flow area smaller than normal.

The second fault is a measurement fault on the fibre consistency in the deculator. A drift fault with a slope of 3.5e-6%/s is added to the fault-free measurement defic.

The third fault introduced is a process fault, in which the filler retention on the wire drops. In the APROS model, the fault is simulated by changing the retention setup for filler from 45% to 40%. Because of the smaller size of the filler compared to the fibres in the stock, the retention rate for the filler is relatively low. The decrease in the filler retention will directly affect the ash rate of the final paper. Although the quality control for the ash rate maintained the paper quality following the set point, the paper machine is running inefficiently. Furthermore, the filler transportation ability is affected considerably. Moreover, since it is difficult to transfer filler to the final product, it will accumulate in the short circulation, which increases the wear of process devices like pumps, pipes, and valves. As a result of the above, a filler retention drop fault can cause serious problems that require detection and identification as early as possible.

As an example, the fault diagnosis results of the 3rd fault scenario are shown below in Figure 3.16. The notation is explained in Table 3.7.

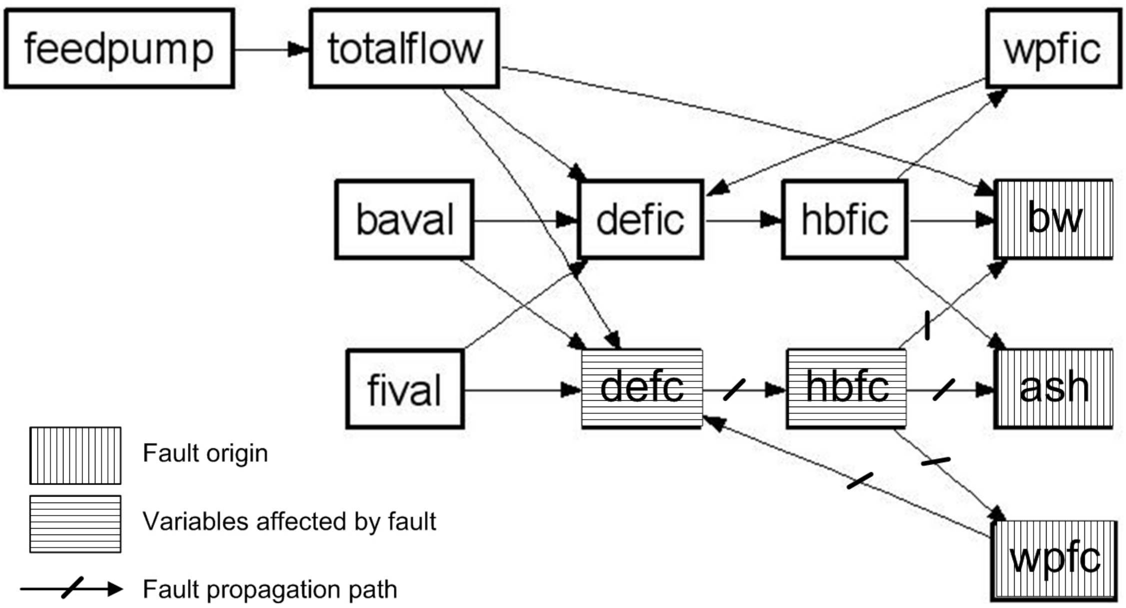


Figure 3.16. Fault diagnosis result for 3rd fault.

Table 3.7. Description of the variables in the short circulation.

Variables	**Description**	**Type**	**Unit**
baval	Basis weight valve opening	Actuator	–
wp_fc	Filler consistency in the wire pit	Measurement	%
wp_fic	Fiber consistency in the wire pit	Measurement	%
fival	Filler adding valve opening	Actuator	–
de_fc	Filler consistency in the deculator	Measurement	%
de_fic	Fiber consistency in the deculator	Measurement	%
hb_fc	Filler consistency in the headbox	Measurement	%
hb_fic	Fiber consistency in the headbox	Measurement	%
feed pump	Headbox feed pump rotation	Actuator	%
totalflow	Mass flow into the headbox	Calculated value	kg/s
bw	Basis weight of paper	Measurement	g/m^2
ash	Ash consistency of paper	Measurement	%

Three fault origins, ash, bw and wpfc, were located, respectively. Moreover, the fault nature rules indicate that it is a process fault, since the fault propagates through the global model.

Using the knowledge matrix approach, two sets of suspected arcs were considered as possible results: {<hbfc, wpfc>, <hbfc, ash>, <hbfc, bw>} and {<hbfc, wpfc>, <hbfc, ash>, <hbfc, bw>, <totalflow, bw>}. The fault diagnosis results provide valuable information in identifying the faulty process component in the case of a process fault. The first arc in the first set {<hbfc, wpfc>, <hbfc, ash>, <hbfc, bw>} is <hbfc, wpfc>, which corresponds to the process components: a wire section and the white water tray. Similarly, the arcs <hbfc, ash> and <hbfc, bw> correspond to the process components: a wire section, a wet press and a drying group. Thus, the suspected process component is the wire section, since it is located on all three arcs. The second set gives the same result. The improvements offered by the new method are highlighted as a summary of comparison of results in Table 3.8.

Table 3.8. Comparison of results between the proposed method and the conventional approach.

Faults	Fault type	Dynamic causal digraph		Novel dynamic causal digraph	
		Fault detection	Fault isolation	Fault detection	Fault isolation
Fault 1	Actuator fault (treated as process fault)	**Nodes**: *defic*, *hbfic*, *wpfic*, *bw*, *ash*	**Fault origin**: *defic*	**Nodes**: *defic*, *hbfic*, *wpfic*, *bw*, *ash*	**Faulty arcs sets**: {<*baval*, *defic*>}, {<*baval*, *defic*>, <*wpfic*, *defic*>} and {<*wpfic*, *defic*>} **Possible faulty components**: basis weight valve hydrocyclone
Fault 2	Sensor fault	**Nodes**: *defic*	**Fault origin**: *defic*	**Nodes**: *defic*	Fault origin: *defic*
Fault 3	Process fault	**Nodes**: *defc*, *hbfc*, *wpfc*, *ash*	**Fault origins**: *wpfic*, *ash*	**Nodes**: *defc*, *hbfc*, *wpfc*, *ash*, *bw*	**Faulty arcs sets**: {<*hbfc*, *wpfc*>, <*hbfc*, *ash*>, <*hbfc*, *bw*>} and <*hbfc*, *wpfc*>, <*hbfc*, *ash*>, <*hbfc*, *bw*>, <*totalflow*, *bw*>} **Possible faulty component**: Wire section

3.6 Measures for maintenance performance

In today's production environments, systems and equipment must perform at levels which were not possible a decade ago. Requirements for increased availability, throughput, product quality, and capability to meet continuously changing production schedules elevate the tempo and intensity of current production. The demand to increase operational effectiveness and revenue while simultaneously reducing capital, operating and support cost are the greatest challenges facing mills and factories. Success in competition requires either cost-advantages or value advantages. Therefore, companies are trying to differentiate from each other with value-adding activities.

This section introduces the concept of Overall Equipment Efficiency, OEE, and its usage as a part of a comprehensive maintenance concept including maintenance measures, corresponding to the measurement system and the solution with interfaces to the surroundings aiming to improve the cost-effectiveness of maintenance practices as well as reducing non-value adding activities inherent in maintenance. The solution combines production and maintenance issues seamlessly together and help managers to control the maintenance as a whole to analyze and develop the domain in the proactive manner.

3.6.1 Approaching measurement system

Performance measurement as a process and the corresponding system are topics frequently used but rarely defined. Literally, performance measurement is the process of the quantifying action, where measurement is the quantification process and action leads to performance. When structuring a conceptual performance measurement system for the cost-effectiveness assessment of maintenance, it is essential to understand some basic definitions and their relations.

Improvements in maintenance practices improve production availability, performance and quality at a certain cost and thus the cost-effectiveness of each action should be assessed. If the profit generated by maintenance is greater than the cost of improvement, then the investment is cost-effective. This is usually achieved via reducing waste and quality defects and losses of breakdown, set-up or adjustments, idling and minor stoppages, reduced speed, quality defects and rework and start ups. The results of these actions improve profitability by having impacts on manufacturing cost, availability, output, low intermediate and product stocks, cost of quality, delivery times, safety issues and energy consumption. There also exists a definite limit for the economical impact of maintenance improvements. Beyond this point, additional investments on maintenance do not give any payback.

3.6.2 Overall equipment efficiency

Overall equipment efficiency (OEE) is derived from the requirements of total productive maintenance, but is now applied widely for the assessment of added value to production through equipment. However, the role of OEE goes far beyond the task of just monitoring and controlling. It takes into account process improvement initiatives, prevents the sub-optimization of individual machines or product lines, provides a systematic method for establishing objectives, and incorporates practical management tools and techniques in order to achieve technical view of availability, performance, and quality.

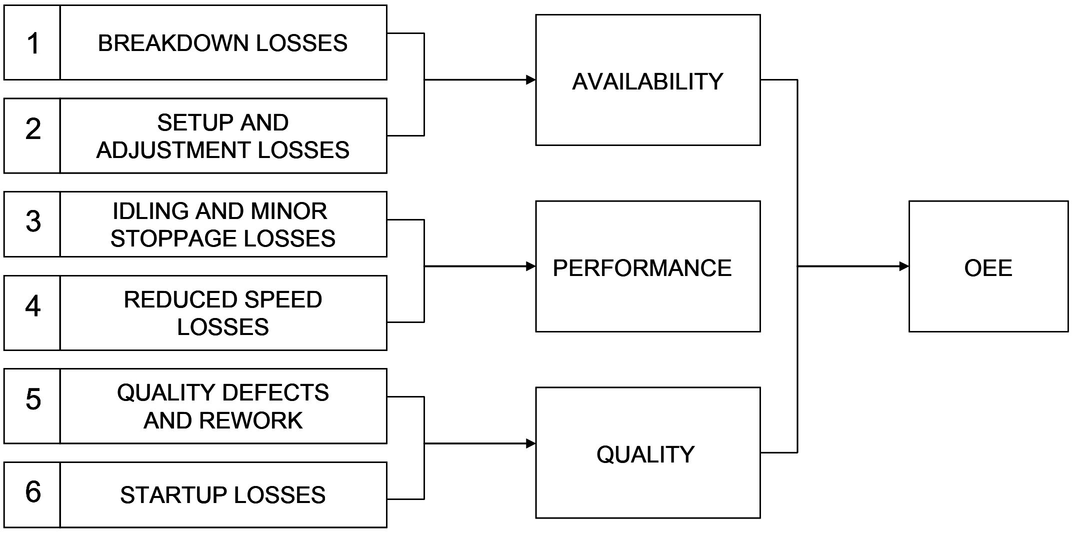


Figure 3.17. OEE and six big losses.

OEE is measured in terms of six big losses (Figure 3.17) which are functions of the availability, performance rate, and quality rate of the machine, production line, or factory, whichever is the focus of OEE application. Thus, OEE is a product of availability, performance rate, and quality rate:

$$OEE = Availability \times Performance\_rate \times Quality\_rate.$$

Generally the term availability describes an ability to be in a state to perform the required function under given conditions at a given instant of time or during a given time interval, assuming that the required external resources are provided. For our purposes, availability means a relation between operating time and planned operating time:

$$Availability = \frac{Operating\_time}{Planned\ operating\ time}.$$

Performance rate is the ratio of actual output to maximum output during the operating time. It can be calculated with the following formula:

$$Performance\_rate = \frac{Output}{Nominal\ production\ capacity \times Operating\ time}.$$

Quality rate is the share of saleable output of the total output produced:

$$Quality\_rate = \frac{Output - Rejected\ output}{Output}.$$

3.6.3 Cost of maintenance

Cost of maintenance is an essential factor in the effectiveness assessment. It brings financial considerations into the technical environment and gives additional and partly new approaches to develop measures for industrial needs. Maintenance cost factors are in Table 3.9.

Table 3.9. Maintenance cost factors.

<table>
<tr><th>Type</th><th>Description</th></tr>
<tr><td>Labour cost</td><td>Labour costs are made up of wages, statutory social security payments and other personnel overheads as well as part of common maintenance costs.</td></tr>
<tr><td>Material cost</td><td>This includes cost of parts and materials used in maintenance. Price, purchase costs, warehousing and handling cost as well as IT and capital cost must also be added.</td></tr>
<tr><td>Common cost and overheads</td><td>These are overall maintenance costs which are not directly allocated to type of work costs:
– costs of maintenance management and planning
– maintenance administration (secretary, finance, purchasing etc.)
– training costs
– costs of data systems and documentation
– rental charges
– capital costs
– other indivisible costs.
Also, part of the company’s common costs is included.</td></tr>
<tr><td>Allocated cost</td><td>Direct costs allocated to a cost centre:
– own maintenance
– maintenance by production personnel
– external maintenance services
– materials.</td></tr>
</table>

For more pragmatic analysis of productivity and maintenance profitability overall equipment efficiency should be used in conjunction with the cost of maintenance. Thus

$$added\_value = \frac{OEE}{\mathrm{cost\_of\_maintenance}}.$$

This formula states how the investments in maintenance activities contribute to OEE and correspondingly what its effects are on the added value. When decomposing OEE to availability, performance and quality even more detailed analysis of maintenance impact on equipment, process or production economy is possible. Additionally, OEE affects directly to the production yield and offers possibilities to construct several ways to estimate high level economical indices as well.

3.6.4 Measurement system

Figure 3.18 illustrates the conceptual maintenance performance system, its major elements, and their relationships to each other. The top tier represents the value added to the production through maintenance activities. The middle tier represents the performance assessment measures including OEE and maintenance cost calculations. OEE divided by maintenance costs equals added value, the top tier value statement. The lower tier of the model represents the various measures related to production measures and maintenance cost assessment. The driving idea is to translate the organization's maintenance strategy and objectives into tangible linkages, interrelationships, activities and measures necessary for effective implementation. The original aim is to link the company's maintenance strategy to short-term measures as the sole indicators of company performance.

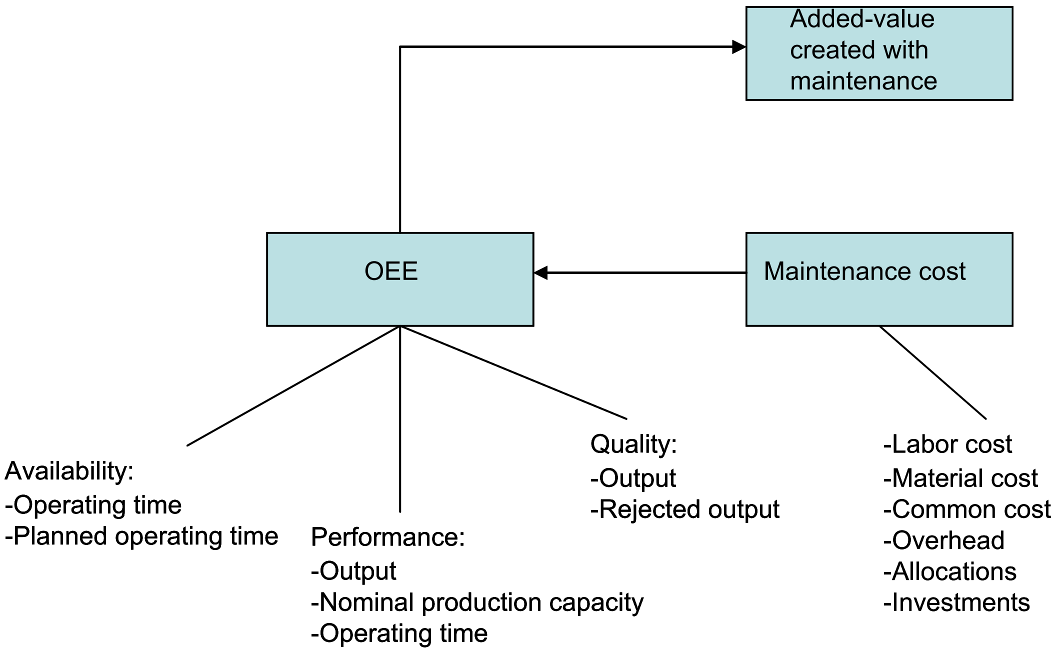


Figure 3.18. Measurement system.

This kind of presentation facilitates the solid foundation to easily examine cause and effects logic such as investments to increase effectiveness. When, for example, new maintenance policy is implemented, it is quite straightforward to analyse the cost structure of new policy and estimate its effects on OEE. This will tell clearly whether the policy is a success or not. Additionally when considering OEE and its close relation to production, it is possible to broaden the examination to cover also high level economical assessments.

The proposed conceptual model connects plant level activities to corporate financials and offers possibilities to easily estimate what-if scenarios. The presented ideas are also quite easily implemented to the new IT-systems, which are capable of connecting separate sources of data and converting data into metrics.

References

Ahola, T. and Leiviskä, K. 2005. Case-Based Reasoning in Web Break Sensitivity Evaluation in Paper Machine. Journal of Advanced Computational Intelligence and Intelligent Informatics, Vol. 9, No. 5, pp. 556–561.

Ahola, T., Juuso, E. and Leiviskä, K. 2007. Variable selection and grouping in paper machine application. International Journal of Computers, Communications and Control, Vol. II, No. 2, pp. 111–120. Available also in: http://www.journal.univagora.ro/?page=article_details&id=77.

Sorsa, A. and Leiviskä, K. 2006. State detection in the biological water treatment plant. Report 31. Oulu: University of Oulu, Control Engineering Laboratory. ISBN 951-42-8274-4. Available in: http://ntsat.oulu.fi/index.php?257.

Sorsa, A. and Leiviskä, K. 2007. State detection of a wastewater treatment plant. In: Proceedings of ESCAPE 17 (17th European Symposium on Computer Aided Process Design). Bucharest, Romania, May 27–30, 2007.

Further reading

APROS. 2008. http://apros.vtt.fi/.

Cheng, H., Nikus, M. and Jämsä-Jounela, S.-L. 2008. Evaluation of PCA methods with improved fault isolation capabilities on a paper machine simulator. Chemometrics and Intelligent Laboratory Systems, Vol. 92, Issue 2, pp. 186–199.

Cheng, H., Nikus, M. and Jämsä-Jounela, S.-L. 2008. Fault diagnosis of the paper machine short circulation process using novel dynamic causal digraph reasoning. Journal of Process Control, Vol. 18, Issues 7–8, pp. 676–691.

Kärkkäinen, T. and Äyrämö, S. 2004. Robust Clustering Methods for Incomplete and Erroneous Data. In: Zanasi, A., Ebecken, N. and Brebbia, C. (Eds.) Data Mining V: Data Mining, Text Mining and their Business Applications. Southampton, UK: WIT Press. Pp. 101–112.

Kärkkäinen, T. and Äyrämö, S. 2005. On Computation of Spatial Median for Robust Data Mining. In: Proceedings of Sixth Conference on Evolutionary and Deterministic Methods for Design, Optimisation and Control with Applications to Industrial and Societal Problems (EUROGEN 2005). Munich, September 12–14, 2005.

Mäyrä, O., Ahola, T. and Leiviskä, K. 2007. Time delay estimation in large data bases. IFAC LSSTA Symposium. Gdansk, Poland, 23–25 July, 2007.

Olli, J. and Koskinen, K. 2007. Structuring maintenance measurement system for performance assessment – a conceptual approach. COMADEM 2007.

Oussama, R.-Y., Gebus, S., Juuso, E. and Ruusunen, M. 2007. Failure mode identification through linguistic equations and Genetic algorithms. Report. Oulu: University of Oulu.

Sorsa, A., Peltokangas, R. and Leiviskä, K. 2008. Real-coded Genetic Algorithms and Nonlinear Parameter Identification. Accepted to IEEE IS2008 Conference, Sept. 6–8, Varna Bulgaria.

Äyrämö, S. 2006. Knowledge Mining using Robust Clustering. PhD thesis (monograph). Jyväskylä: University of Jyväskylä.

Äyrämö, S., Kärkkäinen, T. and Majava, K. 2007. Robust refinement of initial prototypes for partitioning-based clustering algorithms. In: Skiadas, C. H. (Ed.) Recent Advances in Stochastic Modeling and Data Analysis. World Scientific. Pp. 473–482.

4. Business, operations and organizational thinking

By Pertti Saariluoma, University of Jyväskylä

Every enterprise operates in markets. This means that their environment is always dynamic and eventually uncertain. New technological innovations, alternating tastes of the consumers, competitors, market shifts, major economic trends such as business cycles or globalisation make it impossible to live and survive for a firm without constantly developing new ways to react to the new types of environmental challenges. This means that firms must be internally dynamic to be able to respond to the demands of the external changes.

The dynamisms of the markets make it necessary for firms to find new ways of operating. This presupposes organizational thinking, because thinking is the only way to find ways of solving new problems or new ways of working with the old ones. This means that the competence of a firm to survive and be successful depends on firms' economic and mental capacity to find means to respond from its point of view uncontrollably behaving markets. In the very end, the core of the capacity to respond to the demands of constantly complicating economic environments is nothing but firms' capacity to use its resources in an optimal way. This on its behalf depends only on the capacity to think.

Economic activities depend on human capacity to create new means or to use old means in purposeful manners. However, from a psychological point of view, new types of behaving presuppose creating new ways of representing world and this depends always on thinking (Newell and Simon 1972, Simon 1969). This means that in the very end human thinking is always the very last factor that explains what happens to firms. They success and fail depending on their capacity to think.

The first confusion is caused by inexact interpretation of what thinking is. Many people incorrectly claim that organizational thinking is essentially decision making. Decision making means choosing between one or more existing alternatives (Tversky and Kahnemann 1974). However, before one can make a choice between alternatives these alternatives must be worked out in the minds of the decision makers. This means that much before one can make any decision at all, it is essential to have a goal and pursuit towards that goal. Briefly, one can call such goal oriented activity intentional action. This presupposes fining means, which enable a person or organization to formulate and reach their goals. This is possible only if people are able to categorize the situation, and find means to reach their goals. The latter processes have normally be called problem solving and in a wider context designing (Newell and Simon 1972, Saariluoma 2002, 2003).

Decision making is thus only a relatively restricted though important subprocess in organizational thinking.

The second type of confusion rises from incorrect understanding of the role of modern AI and other information tools in organizational information processing. However clearly and evidently human thinking is the core of organizational information processing, one can find much confusion around it. Some people think that modern computational devices can replace human thinking. One may have an illusion of the enormous power of decision support and expert systems. One may think that they can replace human thinking or may provide protection against human errors. To some degree, this idea is true, because good information system enable people to get crucial information to be able to effectively consider and search for solution to the problems. It is also possible to replace in routine matters the need for human work by realizing computationally routine information processes. Nevertheless, all programs and the ways they can be used are outcomes of human creative thinking. Their capacity is in all dependent on their creators' capacity to correct comprehending and designing. They are only tools for human organizational thinking. How they are used and how they should be used depends on how much we understand about organizational thinking.

These two mistakes often make it difficult to understand how information systems could be developed for supporting organizational thinking. The first mistake makes it impossible to get a realistic view to the complexity of organizational thinking, because it sets aside many important presuppositions for analysing rational decision making. If one does not have correct alternatives, it is impossible to make correct decisions. Consequently, the view that organizational thinking is essentially decision making leads the research out of rational paths by closing out or research vast parts of what really takes place in organizations.

The second mistake does easily take us far from understand correctly organizational information processing, since it give too little weigh to human role in it. The consequences may be serious, when human responsibility for organizational thinking is carelessly replaced by blind reliance to decision support and expert systems. It is well known that errors are made when people do not themselves understand, for example, true scale of matters but accept as true information, which may be a consequence of incorrect input values.

For the above type of risks, it has become essential to develop new types of information systems design processes. In these processes, information about human behaviour is collected following the principles of modern human research. It is also essential that the analysis of human roles, human-machine co-operation cultures, and human-system interaction processes are considered on scientific rather than on intuitive grounds.

4.1 Human error

Thinking in economic life, e.g., in process industry is always prone to err. The complexity of the processes increases constantly and therefore seemingly minor mistakes may cause rather difficulty solvable risks. An incompetent person may easily cause substantial losses by careless actions, because long stops in process industry are expensive. This is why it is essential to find in complex chains of thoughts those factors and find means to minimize the number of these risks.

It is not easy to locate the causes of risk, problems and errors and thus to correctly focus the elimination procedures. To get a good hold on these problems it is essential to define some of the most important ground concepts. The leading idea is to investigate the web of actions and to find the strong and risky points in organizational information processing.

In general, the goal for investigating expert and decision support systems is to safeguard organizational information processing. This is why it is essential to find out where organizational information processing can lead to incorrect outcomes. On this ground, it is logical to say that the reason of an error in organizational thinking is the factor which bring an incorrect piece of information to the organizational information processing system (Saariluoma 2003). Of course, a best practice is respectively a method that safeguards the systems against errors.

One can divide errors in organizational thinking and information processing in active and passive. Active errors are realized actions, which do lead inferior to assumed goal. Intel, for example, had an error in one of their chips. After a long time, it was detected by the customers and they reclaimed. Intel was afraid of their costs, refused to compensate, took a legal action, losing half a milliard, and much of its goodwill (Mitroff 2000). Intel planned what it can do, believed that it can intimidate its customers and paid for that. It was an active error.

Passive thought errors are cases in which people do not take an action thought they should. Ericsson did not by Nokia 1992. Five years later it was evident that passive style had been a serious mistake. As so often in case of passive thought errors, nothing could be done any more. This is why passive thought errors are as serious as active, though it is sometimes more difficult to find them in the webs of complex thought processes.

One may think that taking any action, which leads to a worse outcome that has been assumed, is an unfair criterion for an error. There are problems and decision situations, which cannot be fully satisfactorily conceptualised. People did not know that that market situation in Eastern Europe shall change as a consequence of political changes. Therefore, one may think that it is unfair to say that our industry had incorrectly predicted what was to come, though many aspects of so called "Bank crises" can be explained on the ground of the mistaken continuity assumption.

Nevertheless, thought errors are facts and they should be taken as such. One can hardly say that medieval doctors treated their patients correctly. The explanation of an error may be lack of knowledge, but this reason is equal to some other. If one wishes to reach as high-level organizational thinking and information processing as possible, it is essential to find out all the relevant information.

4.2 Limited capacity

When we have to find explanations for human decision and thought processes limited memory capacity has often proven to be valuable. Human memory is divided into several subsystems. The most important two of them are working memory and long term memory. By working memory we refer to the part of human memory which is actively involved in maintaining memory information during ongoing task. If I call to someone, I keep the number and the way I use my phone in my working memory during the performance of this task. Long term memory is instead the unlimited mass of knowledge each human being has learned during the lifetime. It may contain knowledge from the first school building to the relatives of ones spouses or grammar of languages one knows.

It has been empirically demonstrated that all people have around similar size of working memory (Atkinson and Shiffrin 1968). Its capacity is to keep active 4–7 unrelated pieces of information. This is a really small number, but fortunately people have mechanisms to circumvent this immediate limit of working memory.

It has been show that people can remember equally many letters as words. However, the list of words entails much more letter than the unrelated letters. This means that it is possible by means of organizing the memory representation to store much more information in working memory than it is possible with the unorganized materials. Actually, there is no limit for the size of a memory unit of chunk and therefore the capacity of four chunks can store very variable amount of information. Experts, for example, can remember numerous chess games which have been verbally presented them. Similarly, all people are much better to remember their professionally important information compared to matters they are novices.

Nevertheless, human working memory capacity is limited and it has been empirically demonstrated that people may make severe thought errors for this reason. In problem solving as well as in problem solving and design tasks people may easily err, because they forget something very obvious. In many cases, the explanation is that this particular piece is lost in working memory.

The importance of limited capacity can be seen for example in the fact that people do not normally consider but a few alternatives in decision and problem solving situation with thousands of possibilities. This means that human mental representations are severely limited and that this factor has sometimes negative consequences for information processing in human machine interaction.

4.3 Problem solving and design thinking

Before it is possible to understand what happens in human decision making it is essential to have a clear idea about problem solving and design thinking as well as such precondition of their as categorization. If one does not comprehend these thought processes, any ideas about decision making remain narrow and vague. In organizational thinking, the main human thought processes are intervened by each other, but problem solving theories express most accurately how people form their ideas about decisions they need to do.

Problem solving is a thought process which emerges when people have a goal, but they have no immediate means to reach it. Problem solving is thus a process which provides people with means to reach definite goals (Newell and Simon 1972). Often the goal is to find out the very goal for some future activity. A good example is to find a business idea or product conceptualisation.

Design thinking is a form of problem solving. Normally, design thinking concern such issues as business plans, new products, and marketing campaigns. This means that design thinking is the name for core business thought processes. The function of design thinking in organizations is to create new information.

From the current point of view, design and problem solving processes are manipulation of mental representations. In one moment of time the representations present some state of affair and a little later this state of affairs has changed. Finally, it gets its ultimate form. The analysis of this process and the principles it entails is essential for getting a clear idea about what kind of expert systems and decision aids are required in industry.

Problem solving precedes any decision making, because it is necessary to have firstly a representation of decision alternatives. Therefore, it is essential to investigate in detail the involved mental contents before any analyses of decision processes. How people design the decision situation for themselves is essential for correct investigation of decision making. The answer to the questions, what kinds of mental contents form the core of the decision representations, what their origins is and how they are organized is decisive for understanding what happens when people make organizational decisions.

Today, we know that mental representations have highly articulated structure. People do not consciously represent but small compact part of among all the possible alternative actions. Very interestingly, these organizations are sense making. In architectural design the architects are guided by small sets of functional rules. They orientate a bedroom window towards west because the sun rises in east (Saariluoma and Maarttola 2003). All of architectural design is guided by reasons that are not always explicit but nevertheless mostly explicable.

We can find similar reasons also in engineering design. Extended nip, in paper machine, the design process of which we have been reconstructing, was initially designed to increase the press impulse on wet paper web and thus improve water removal and eventually make paper production faster. Functional rules or reasons apparently have an important role in explaining how chunks are linked to each other. This means that understanding how the elements of some mental representation make sense is often decisive for understanding why people act in suboptimal manner.

To appreciate why it might make sense to make a certain kind of construction, we have to keep in mind what the design elements and their properties are. We must know how these properties and elements are mentally represented by designers, because designers may make false assumptions with respect to the crucial objects and their properties. This is a presupposition for understanding the structure of mental contents.

4.4 Decision making

Decision making is slight different thought process from problem-solving and design. Decision making processes arise when a human being has two or more alternative courses of action but they cannot make all of them. Decision making is thus choosing between alternatives. However, alternatives have also their attributes and we must consider them before it is possible to analyse human decision making as a whole.

We can divide alternatives into two main types. In some cases, we know certainly what the consequences of the selection are. This kind of decision is deterministic. If we know only for some probability what the consequences of the decisions are, we call decision probabilistic and it is made in conditions of uncertainty. In industry, we quite commonly work under uncertainty, because we do not have complete information about the prevailing state of industrial processes. To solve the problems of uncertainty, people need often tools which help them in collecting, analysing and sampling information which reduces their uncertainty.

There are also many attributes of decision situations which are closely liked to decision maker. People combine in variable ways their hopes, values, wishes, utilities, goals and other desires. They have also different beliefs concerning the situation. Their expectations, expertise, and available means vary very widely. They follow different decision rules and strategies. This means that there are numerous factors which influence people when they make decisions.

Firstly, the nature of decision situations is critical when we think correct decision making. The quality of decision depends on the information people have about the environment and the phenomenal processes they have to make decisions. If the phenomena are not well understood, and the knowledge is probabilistic instead of lawful and deterministic phenomena, the quality of decisions decreases and decision control becomes low. Business activities provide numerous examples about poorly understood and uncertain environments. If we have lawful information as in many cases of physical analysis of industrial phenomena, decision circumstances are more certain and the risks of erring decrease.

The quality of decisions depends also on the way the way information is presented to people may influence on the actual decision process in several manners. Unclear and emotional ways of presenting information make rational decision making difficult. When people are given same information in two different manners there may be substantial differences is the preferences. Famous example is about unusual Asian disease (Tversky and Kahnemann 1981).

> Group A: was given the following information:
>
> Problem 1: Imagine the USA is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequence program are as follows:
>
> If program A is adopted, 200 people will be saved.
>
> If program B is adopted there is 1/3 probability that 600 people will be saved and a 2/3 probability that no people will be saved.
>
> Which of the programs you favour?

Group B: Same background scenario.

If programme C is adopted, 400 people will die.

If programme D is adopted there is 1/3 probability that nobody will die and 2/3 probability that 600 people will die.

Which of the programs you favour?

The two problems are identical with exception of how they are presented or framing. Nevertheless in Group A 72% chooses A and in Group B 78% chooses D. The presentation of the problem leads to different and opposite outcomes. The explanation is that people choose risk searching strategies to avoid killing some people. Of course, it is vital to find right framing to problems, when developing industrial information systems.

Human factors form the final important factor in decision making. The quality of decisions depends on how well people understand the situations, what their domain specific skills are and finally what kind of decision strategies they follow. Experts have domain specific skills. They have been in the field over a decade and thus they have learned to discriminate relevant knowledge. Experts make decision faster than novices, because they have a vast storage of task specific knowledge making them able to make more rational decisions in their own field (Ericsson 1996, Newell et al. 2008).

Strategies of making decisions vary. Some people are risk searching and some are risk aversive. The first group likes to take big risks to reach a really positive outcome, while the second group is rather avoids possibilities of harms and negative outcome thought the consequences and prospects were less satisfactory. A well known example making the difference is following:

Group A: Choose between (1) .001 change of winning 5000 $; (ii) 5$ for sure.

Group B: Choose between (1) .001 change of losing 5000 $; (ii) losing 5$ for sure.

In Group A 72 percent of people choose (1) and in group B 83% choose (ii). This means that people are risk searching for gains and risk avoiding with losses (cited from Newell et al. 2008). Of course, in developing decision aids it is essential to understand expertise and framing type effect. A first step towards this direction shall be presented later, when sc. cognitive biases are discussed in Chapter 5.

As a whole, one may say that human decision making does not follow idealized probabilistic decision models. Therefore, many difficulties with implementing decision aids could be avoided, if the complexities of human decision behaviour can be effectively harmonized with the possibilities of decision aid systems. Especially important shall be correct understanding of decision errors.

4.5 Decision errors

Originally it was thought that people are very good at intuitive decision making. They could relatively well assess probabilities and utilities in simple situations. However, the experimental situations in these experiments were relatively simple and entailed very little semantics or mental contents. Subsequent research illustrated that the understanding decision processes is far from simple.

In the 70's, it was nevertheless showed in a number of experiments that people are apt to make very serious errors in decision situations. These errors were systematic and typical to the experimental conditions and therefore they were called decision illusions. Systematic empirical research illustrated that psychologists could find numerous illusions. As a whole it was evident that human beings were far from intuitive scientists or ideal decision makers.

Typical examples of external factors which could cause people to miscomprehend true utilities were anchoring or visibility. Extreme examples could bias human decisions surprisingly effectively. If they were give examples with very extreme values, they easily generated this to very different types of cases. The phenomenon was called anchoring, because the first examples made subjects to bias their estimated towards the original anchoring value. Visibility heuristics makes people to think that very well known phenomena are more probable than they actually are (Tversky and Kahnemann 1974).

Numerous important decision illusions have been demonstrated over the years. In addition to the ones such as framing effects discussed already, there are many biases caused by incorrect information organization. Different types of conjunction illusions provide a good example of such problems. Linda is the famous case (Gavanski and Roskos-Ewoldsen 1991, Tversky and Kahnemann 1982):

> Linda is 31 years old, single, outspoken and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations.
>
> What statement is more probable?
>
> 1) Linda is a bank teller.
> 2) Linda is a bank teller and an active in the feminist movement.

Here, 86% of subjects took the latter statement more probable. However, in normative sense this is incorrect interpretation and a bias, because a conjunction of two sets is always smaller than any of the sets in conjunction alone. More clearly, the set of bank tellers is larger than any of its subsets.

We know also that emotional factors may substantially influence on the quality of human decision making (Hastie 2001, Zajong 1980). Emotional states may loose self control, lead it to less rational targets, bias belief and their systems, and they may affect on risk talking in various ways. Moreover, they may make people to over concentrate to some alternatives and neglect some others or polarize their decision spaces. They may distort moral aspects of social decision making or improve the standards of moral behaviour. Emotions may also make decision making aversive. In sum, emotions have substantial effects on decision making, but these effects are not straightforward. They may in different occasions impair the quality of decision making, but very commonly their effects are positive.

The most critical aspect of emotions is the forming of emotional preferences (Zajong 1980). One of the main functions of emotions in human mind is to evaluate the value of objects and situation for a human being. People choose objects and people they like and they feel to be attractive. Very easily these emotional preferences overrun any rational considerations. Forming emotional preferences need to be in any relation to rational inferences (Zajong 1980). In business management, this phenomenon is attempted to be controlled by avoiding "hot cognitions". This may mean, for example, maintaining a calm discourse culture, which allows people to think rationally.

An additional example of decision biases is overconfidence (Oskamp 1965). When we study how confident people are of their decision, it is possible to noticed that they sometimes are over confident with respect to their own conceptions. The do not search for falsifying evidence or consider in detail the possible hypotheses (Oskamp 1965, Wason 1967, 1983). As a consequence of their over (and in fact under) confidence they may make severe errors.

Finally, we can take perhaps the most famous error in group decision making. This is called group thinking or groupthink (Janis 1972). In a group with one authoritarian person, it is often the case that the group does not consider all the alternative and consequence, because people do not dare or want to raise important issues on the table. Kennedy administration, for example, underestimated the risk of Cuban invasion. Though groupthink may have positive effects, it may also lead to serious errors (Choi and Kim 1999).

There are two interrelated major problems involved in human decision making. Firstly, the limited working memory capacity makes it impossible for human beings in real life situations to construct exhaustive mental representations of decision situations. Consequently, people have to make "samples" or abstraction of in the sets of actual decision influences factors. They have to take only a few alternatives among all imaginable and they can only encode some utilities, beliefs, desires or other decision attributes.

Secondly, the limited size of mental representation compels people to construct representations, which they think to involve all relevant knowledge. For several reasons, the problem of constructing ideally relevant mental representations may fail and people may make decisions about incorrect issues. The research in biases illustrates in an effective manner, how easy it is for people to err in making decisions.

People may thus err as a consequence of misrepresenting the decision situation (Saariluoma 1990, 1992). Their "sample" of reality may be irrelevant or misplaced thinking the true nature of reality. Consequently, they may end to incorrect and poor decisions, though the objective situation would not require surpassing the limited information processing capacity.

The presented pocket introduction to some problems of the psychology of human decision making should make it evident that decision making is very complex process with numerous possible courses and outcomes. This means that it is impossible to make categorical statements concerning decision making in industrial decision contexts.

4.6 Decision making in human-machine interaction

Human-machine interaction is one of the most important applications for the psychology of decision and thinking. The reason for this is in the problems of controlling complex technical processes. When people operate with such complex objects as aircrafts or paper machines, they have to have mental representations for the behavior of these objects (Holnagel 2005). They have to be able to predict how the controlled machine reacts to what they do. Otherwise the risks in decision making very swiftly rise. However, human performance capacity is relatively limited and especially in new or odd situations this may lead to severe errors.

One may ask here, why decisions are critical. The explanation is quite straightforward: People are normally in human-machine interaction the element which duty is to make the decisions. If in some part of the machine-aided production process does not require decision making, it is easy to realize by machine. Unfortunately, machines are poor often decision makers. If we think, for example, a Turing machine to make the discussed theoretical point clearer, there are two things it cannot make. Firstly, it cannot select which elements in a table are relevant. It simply does not have any notion of relevance.

On general level, we can analyze and explain human interaction with machines in terms of task complexity. In this way, it is possible to abstract the details of current human machine interaction problems and discuss what human problems are like. Of course, any abstraction based on the concept of complexity loses details but it makes the discussion on decision making and thinking applicable to any human-machine interaction process. The low level details can be coped with empirical analysis concerning the particular environment. Decision making and thinking in human-machine interaction is thus be seen as the problem of meeting complex environment.

As has been reviewed, above human performance capacity sets the most important risks and limitations for the rational organization of human-machine interaction. People are apt to err, human errors cannot be eliminated as long as people are part of machine systems and these errors are costly. To be precise, human errors cannot be eliminated even in imaginary machine systems with complete automation and no human involvement, because these machines are eventually designed and constructed by people. Even scifi-machines designed by machines designed by people cannot avoid the possibility human errors. Human errors are always a part of human machine interaction and for this reason it is essential to analyze human component in realistic and scientific psychological methods, concept and understanding. Everyman's folk-psychological intuitions do not lead anywhere.

The fact that people make errors does not mean that human errors are unavoidable. Their probability can be essentially reduced by rational psychological means. It is possible to educate people, it is possible to make interaction simpler for people and finally, it is possible to move complex task-elements over to be performed by carefully tested machine elements. This means that the complexity of the task is reduced from human point of view. Consequently, the risk of erring can be reduced.

The first question in applying complexity based thinking is to clarify what the basic concept means and how we should apply it in the context of decisions in human machine interaction. In literature, the normal way to think separately factors which in machine makes things complex to people and also factors that in human thinking may complicate the use of the machine. A simple example of the first mentioned issues is a menu with too many and confusing links and about the latter novice mental representation of a complex machine environment. The former type of problems must be eliminated by means of simplifying e.g., the menu structures by emphasizing the essential routes to unessential or effective application of macros. Moreover, it is essential to more over to machine even complex routine issues whenever, it is possible. Much of the present work is concentrated to this latter way of responding machine complexity. The most important manner to eliminate complexity causing factors in people is teaching. People can be thought the most cognitive ergonomic strategies of acting in interacting with an interface. Nevertheless, these two points deserve some elaboration.

The most important issue is that we cannot consider human and machine separately, when we reduce thought and decision risks in industry. The notion of “joint cognitive system” was developed to express the necessity to integrate machine improvements with improvements on human dimension. The user related functions of machines must be organized in an effective manner to simplify the decision situations for the users. Otherwise, there is always a risk that realizing the decision task with a machine actually biases the decision relevant and critical information processing.

It is important to keep in mind that people have two functions with machines. Firstly, they have their own action goals, which they realize with help of machines. Secondly, they often have to be responsible for the ultimate performance of the machine. This means that they have to have two sectors in their mental representations. These sectors are what to do and how to get it done. The latter can easily cause problems in performing the former and in these cases the machine aided decision operations can be poorly performed.

References

Atkinson, R. and Shiffrin, R. (1968). Human memory: A proposed system. In: K. W. Spence and J. T. Spence (Eds.) The Psychology of Learning and Motivation, Vol 2. New York: Academic Press. Pp. 89–195.

Choi, J. and Kim, M. (1999). The organizational application of groupthink and its limitations in organizations. Journal of Applied Psychology, Vol. 84, pp. 297–306.

Ericsson, K. A. (1996). The acquisition of expert performance. In: K. A. Ericsson (Ed.) The road to excellence. Mahwah: Erlbaum.

Gavanski, I. and Roskos-Ewoldsen, D. (1991). Representativeness and conjoint probability. Journal of Social Psychology, Vol. 61, pp. 181–194.

Hastie, R. (2001). Problems of judgement and decision making. Annual Review of Psychology, Vol. 52, pp. 653–683.

Holnagel, E. (2005). Human reliability assessment in context. Nuclear Engineering Technology, Vol. 2, pp. 159–166.

Janis, I. (1972). Victims of groupthink. Boston, MA: Houghton and Mifflin.

Mitroff, I. (2000). Tartu oikeisiin ongelmiin. Helsinki: WSOY.

Newell, A. and Simon, H. A. (1972). Human Problem Solving. Engelwood Cliffs, N.J.: Prentice-Hall.

Newell, B. R., Lagnado, D. and Shacks, D. (2008). Straight choices. Howe: Psychology Press.

Oskamp, S. (1965). Overconfidence in case-study judgments. Journal of Consulting Psychology, Vol. 29, pp. 261–265.

Saariluoma, P. (1990). Apperception and restructuring in chess players' problem solving. In: K. J. Gilhooly, M. T G. Keane, R. H. Logie & G. Erdos (Eds.) Lines of thought: Reflections on the Psychology of Thinking. Wiley: London. Pp. 41–57.

Saariluoma, P. (1992). Error in chess: Apperception restructuring view. Psychological Research, Vol. 54, pp. 17–26.

Saariluoma, P. (2002). Ajattelu työelämässä. Helsinki: WSOY.

Saariluoma, P. (2003). Apperception, content-based psychology and design. In: U. Lindeman (Ed.) Human behaviour in design. Berlin: Springer. Pp. 72–78.

Saariluoma, P. & Maarttola, I. (2003). Errors and functional reasons in architectural design. Journal of Architectural and Planning Research, Vol. 20, pp. 344–354.

Simon, H. A. (1969). The sciences of artificial. Cambridge, MA: MIT Press.

Tversky, A. and Kahnemann, D. (1974). Judgement under uncertainty: Heuristics and biases. Science, Vol. 185, pp. 1124–1131.

Tversky, A. and Kahnemann, D. (1981). Framing of decisions and the psychology of choice. Science, Vol. 211, pp. 453–458.

Tversky, A. and Kahnemann, D. (1982). Judgements of and by representativeness. In: D. Kahnemann, P. Slovic and A. Tversky (Eds.) Judgement under uncertainty: Heuristics and biases. Cambridge: Cambridge University Press. Pp. 84–98.

Wason, P. C. (1967). On failure to eliminate hypothesis. In: P. C. Wason and P. N. Johnson-Laird (Eds.) Thinking and reasoning. Harmondsworth: Penguin Books.

Wason, P. (1983). Realism and rationality in the selection task. In: J. St. Evans (Ed.) Thinking and Reasoning. London: Routledge and Kegan Paul.

Zajong, R. (1980). Feeling and thinking: Preferences need no inferences. American Psychologist, Vol. 35, pp. 151–175.

5. A collaborative viewpoint on operational decision making

By Kristiina Hukki, VTT Technical Research Centre of Finland

As process industries are increasingly networking with their suppliers, industrial partners, and customers, the recent changes in organizations, workplaces and work have increased the importance of competence and knowledge in modern complex production environments. Therefore, intensive interaction between the different stakeholders requires new types of coordination, co-operation, and collaboration (Koskinen et al. 2005). This development makes it necessary to pay more attention to the collaborative nature of operational decision making. Understanding the significance of human interaction in paper production work is a prerequisite for the successful development of support for decision making.

In this chapter, operational decision making is considered from the collaboration point of view, as distributed among people representing different roles in paper production. The consideration is based on a holistic and systemic approach to complex collaborative work. The approach has been developed and used in studies concerning other contexts of complex work (see Further reading) but can be applied to the field of paper production as well. The approach represents a psychological point of view on distributed operational decision making. The way the decisions are made is considered to be the result of interactions among the persons contributing directly or indirectly to the decision making. The interactions are considered from the knowledge sharing and transfer point of view. The persons having different roles and interconnected tasks are regarded here as actors within a social network contributing to an operational area of papermaking. The extent of the network to be considered can be chosen according to the needs of the analysis, from part of a single production line up to a network crossing organizational and national borders. Decision making in this kind of actor network is highly dependent on the effectiveness of the interactions.

The approach provides means for analyzing the interactions and identifying factors that promote effective collaboration in the network. The knowledge of the promoting factors can be utilized in the development of support for distributed operational decision making, in the form of collaboration practices and IT support.

The chapter is organized in the following way. First, the characteristics of current collaborative work in paper production are described shortly in Section 5.1. After that, the way of analyzing distributed operational decision making by applying the actor network approach is introduced in Section 5.2. Finally, possibilities to develop support to distributed operational decision making with the help of the results provided by the analysis are discussed in Section 5.3.

5.1 Requirements of collaborative work in paper production

The following general level description deals with the requirements that collaborative work in paper production sets for the personnel. The description has been made by utilizing selected references (Leppänen 2001, Laukkanen 2008) concerning work in paper production.

The complexity of the paper production process as a working environment requires collaboration. The process is controlled by a collective subject that is more comprehensive than one crew. In addition to communication and co-operation within one operator crew, information has to be exchanged with the other crews of the same production line, due to delays typical to the process. Communication and co-operation exist also between the crews of the related production processes, for example pulp mixing, and between the personnel in production, production planning, maintenance and quality control. The competence in teams is more important than individual competences and skills.

A paper production line is a very complicated process both in terms of the raw materials, which include e.g. fibres and chemicals, and in terms of complex processes and equipment like a paper machine. The interactions in the process are complex, and the final quality of the paper is a complicated and nonlinear combination of raw material recipes, equipment and process parameters, process control settings and operator actions. There are substantial time delays and recycles in the process, which is integrated and thus makes real-time process control challenging. For process control purposes there are not enough reliable on-line measurements. Process control actions in many sub-processes are still based on indirect measurements and, in many cases, on the skills and experience of the operators, instead of advanced automatic control concepts. This all increases the role played by the knowledge and skills of the operators.

Exchange of information in the critical phases of work processes, e.g. during production disturbances, requires mutually accepted concepts. Common concepts and sufficient knowledge of the work process are also prerequisites for learning from the process events, and for sharing experiences and knowledge in the work community, in order to improve the work process further.

The traditional distribution of work in paper production has not supported the formation of joint conceptual models among the group of workers because, at the beginning of their career, the workers have been able to get only information about some part of the process while working in their limited control district. Despite the demand for cooperation in paper production, the distribution of work has been based strictly on vacancies. Every worker has had his/her own “slice” of the production process to control. Career advancement has also been strictly regulated. During their work careers, workers have proceeded from the finishing of paper to the paper machine, and from the dry end of the machine to the wet end. Only the machine operators working at the wet end have been working on the whole area of the process and have attained a better conceptual mastery of the process than the other professional groups.

The situation is now changing. One of the major top-down changes in the local production environment is that local production teams now have important roles and responsibilities in the global business processes. The use of global processes and ERP systems has shifted some work previously done by line managers to the production teams which now form an integrated part of the global delivery chain.

The development of enterprise level business processes has remarkably changed the role and the competence requirements of local production teams. In a modern paper production unit the importance of the operator's skills, knowledge and degree of motivation will make a difference in the profitability of the production line. The role of operation teams in paper production units has changed from that of a workforce into a group of multiskilled profit makers who are optimizing the operation and profitability of the production line based on knowledge and information in different systems and processes. The purpose of the production personnel is to assess, adapt and control the production line manufacturing process and maintenance activities to meet the business production plan and product specification. Production personnel will continuously need to identify opportunities for improving process operations and the work environment, to detect and remove any threats in stationary operations, to compensate and correct abnormal situations and to ensure that after disturbances the production will be brought back to the normal operation level.

Working in production teams requires a cross-disciplinary, comprehensive conceptual understanding of the whole production chain, covering major processes at different levels. The changes also emphasize the need for a higher educational level and efficient organizational learning in production teams.

On the basis of the description above it can be concluded that the personnel contributing to paper production should fulfil at least the following requirements regarding their competences and working practices:

- shared understanding of essential issues concerning paper production among the personnel
- multi-skilled expertise of operator and maintenance teams
- awareness of business strategies in all organizational levels
- unified working practices within and among production lines.

Development of these competences and practices at the mills requires analysis of collaboration in paper production and recognition of issues that promote effective interaction among the personnel. The promoting issues are important since they lay a basis for effective operational decision making. Application of the actor network approach, discussed in the next section, provides means for identifying these issues.

5.2 Actor network approach to analysis of operational decision making

In the following, the principles of the actor network approach are introduced on a general level by using quality control in a paper production line as the context of description. This context has also been used in a case study concerning the development of collaboration at a paper mill (see Further reading).

The approach regards quality control as the collective performance of an actor network taking care of a common goal. At the paper mills the general goal of the persons contributing to quality control in a production line is to fulfil the requirements set by the business strategy of the enterprise and by the defined quality goals of the products. According to the approach, it is useful to choose and define a concrete, operational goal for the network in order to be able to make the connections of the actors' practical work tasks with the business goals and quality goals more visible. The definition is made by identifying the most important general level operational goal in quality control from the enterprise's business strategy point of view. An operational goal defined in this way is here called the operational core task. An example of a core task in quality control is brightness control.

The concept of a collectively performed operational core task provides a feasible framework for considerations of distributed decision making in the actor network. The actors in the network contribute to the performance of the core task in different ways, according to their roles. Some of them are responsible for operational decisions but may need the contributions of other actors in order to gain an understanding of the situation and to make the decision. These contributions can be in the form of giving information or participating in discussions on the situation and the decisions to be made.

A shared understanding of relevant issues is a necessary prerequisite for effective interaction among the contributing persons. The crucial point is what these relevant issues are. One important issue is that the persons have a shared understanding of the systemic whole that they are operating. This means comprehension of the fundamentals of paper process dynamics as a whole and the mutual influences of the operations made in different parts of the production line. Another equally important issue is a shared understanding of the systemic whole the persons are participating in, i.e, the operational network. Due to the connections between the actors' tasks the decisions made in the network influence each other. Decisions made by one actor may set constraints on the other actors' possibilities to act.

A more profound understanding of the interactive nature of operational decision making facilitates comprehension of the interdependencies between the decisions and makes it easier to anticipate the consequences of the operational actions. A better understanding of the significance of the ways of interacting on product quality facilitates comprehension of the significance of one's role as part of the collaborative whole. An understanding of the influence of the quality of the work process on the quality of the resulting product is the basis for creating a more profound and unified conception of quality at the paper mills.

Gaining this kind of shared understanding requires common conceptual frameworks for the actors of the operational network. Development of these frameworks is discussed in the following section.

5.3 Development of support to distributed operational decision making

The necessary shared understanding required by effective interaction, identified in the preceding section, can be promoted at paper production enterprises both by developing collaboration practices and by making improvements to the existing knowledge and performance support systems.

In order to improve collaboration practices in operational decision making the strategically important operational core task and the actor network, responsible for the performance of the core task, should be defined in the enterprise. After that, shared conceptual frameworks should be developed for the network to guide collaboration in a way that makes it easier to reach the operational goals and meet the business requirements of the enterprise in carrying out the core task.

The frameworks are descriptions that can be used for handling essential issues concerning the decisions. It is important that the descriptions are developed collectively, by combining the different expertise represented in the network.

If the defined operational core task is, for example, brightness control, shared frameworks can be used to enhance the understanding of the overall process dynamics related to production of brightness and to support handling of problem situations concerning achievement of the targeted brightness values. Simplified general level descriptions can be made to present the influences of the operations on the process in different parts of a specific production line. Different types of diagnostic information concerning brightness can be described by presenting checkpoints of brightness along the production line. The descriptions can be presented in the form of flowcharts, graphs, tables, etc.

The descriptions facilitate comparison of alternative ways of achieving the quality goals and definition of the best operating practices. Use of the descriptions as shared frames of reference in training and quality meetings and during test trials support discussions on

- anticipated consequences of different operational decisions and combinations of decisions from the quality, effectivity and economic points of view
- diagnostic possibilities and constraints concerning relevant information required for the decisions
- uncertainty related to anticipating and diagnosing.

It is important that the models are developed on the basis of collaboration of the representatives of relevant organizational units and work domains. By providing a forum for comparing the views of persons representing different positions the descriptions are assumed to

- improve understanding of the interdependences between the work tasks in the production line and the consequences and boundary conditions of the decisions
- generate common concepts concerning the quality of the product
- enhance understanding of the significance of the quality of the work process on the quality of the product and the significance of one's contribution as part of a collaborative whole
- facilitate integration of business strategy to daily work and enhance cost-awareness
- enhance mutual understanding and multi-skilled expertise
- facilitate making tacit knowledge more explicit
- contribute to more unified work practices.

In addition to the development of collaboration practices, distributed operational decision making requires decision support that coordinates the work of the actor network on different hierarchical organizational levels. At the paper production enterprises improvements to the decision support could be made by codifying knowledge gained through the development of the shared conceptual frameworks and collaboration practices, described in the preceding section, into the existing knowledge and performance support systems.

The systems as a whole should provide integrated support to network-based collaboration and cooperation by, for example

- presenting the developed conceptual frameworks
- providing access to the frameworks and possibilities to handle and exchange opinions and experience concerning them
- contextualizing the afforded knowledge by linking it to relevant shared models whenever appropriate
- presenting the knowledge in an understandable form.

References

Koskinen, T. et al. 2005. Collaboration and Interaction Functions of Future Process Control Systems. Automaatio 2005 -seminaaripäivät, Helsingin messukeskus 6.–8.9.2005. Helsinki: Automaatioseura ry. S. 287–292.

Laukkanen, I. (2008) Knowledge Transfer and Competence Development in Complex Paper Production Environment. Doctoral Dissertation. TKK Dissertations 103. Faculty of Chemistry and Materials Sciences. Espoo: Helsinki University of Technology.

Leppänen, A. (2001) Improving the Mastery of Work and the Development of the Work Process in Paper Production. Relations Industrielles – Industrial Relations, Vol. 56, No. 3, pp. 579–609.

Further reading

Hukki, K. 2008. Collaboration as a quality factor in paper production. Research report VTT-R-06706-08, VTT: Espoo. (In Finnish.)

Hukki, K. and Holmberg, J.-E. 2006. Systemic approach to risk-informed management of nuclear power plant fire situations. Research report VTT-R-06-00074. VTT: Espoo. (In Finnish.) http://www.vtt.fi/inf/julkaisut/muut/2006/SAFIR_palotilanteiden_hallinta_raportti_120906.pdf.

Hukki, K. and Holmberg, J.-E. 2006. Interdisciplinary development of risk-informed management of fire situations. In: Räty, H. and Puska, E. K. (Ed.) SAFIR. The Finnish Research Programme on Nuclear Power Plant Safety 2003–2006. Final Report. VTT Research Notes 2363. VTT: Espoo. Pp. 361–370. http://www.vtt.fi/inf/pdf/tiedotteet/2006/T2363.pdf.

Hukki, K. and Holmberg, J.-E. 2007. Systemic Approach to Development of Risk-Informed Management of NPP Fire Situations. In: Proceedings of Joint 8th Conference on Human Factors and Power Plants and 13th Annual Workshop on Human Performance / Root Cause / Trending / Operating Experience / Self Assessment (IEEE HPRCT). Monterey, CA, USA, 26–31 August 2007. (CD)

Hukki, K. and Pulkkinen, U. 2004. Systems Intelligence in Expert Interaction. In: R. P. Hämäläinen and E. Saarinen (Eds.) Systems Intelligence. Discovering a hidden competence in human action and organizational life. Systems Analysis Laboratory Research Reports A88. Espoo: Helsinki University of Technology.

6. IT infrastructure for decision-making

By Ilkka Seilonen, Pekka Aarnio and Kari Koskinen, Helsinki University of Technology

6.1 Introduction

From the viewpoint of decision-making the role of information systems is to provide the functionality for decision-support and the data and knowledge required by the decision-makers. The information systems currently used in manufacturing and process industry for MOM have limitations in their capabilities for supporting decision-making. If these systems are to be developed for enhanced decision-support in the future, the application of selected new information technologies might be useful.

6.2 Existing IT systems

Maybe the most essential information systems in manufacturing operations management include Manufacturing Execution Systems (MES) and Enterprise Asset Management Systems (EAM). MES provides functionality to support some selection of different activities in production, inventory and quality operations management. EAM provides functionality to support of maintenance of the physical assets of a company. They are connected to related information and automation systems of a company, e.g. Enterprise Resource Management systems (ERP), Distributed Control Systems (DCS) and Condition-Based Monitoring systems (CBM). ERP provides functionality for business and logistics management of a company, DCS functionality to control and monitor continuous production processes and CBM functionality to monitor the condition of physical equipment. In addition to the previously mentioned systems, companies may also have other related information systems, e.g. Laboratory Information Systems (LIMS), Production Information Systems (PIMS) and Advanced Planning Systems (APS). Sometimes these systems are part of MES or DCS.

MES supports the work of human workers relating to the activities of MOM (level 2 in IEC [2003a]). Examples of MES include TIPS (Tietoenator Integrated Paper Solution) and metsoDNA MES and Simatic IT. The functionality of a MES typically supports the following activities: order handling, production management, inventory and delivery management, quality management, cost management, analysis and reporting, and process information management.

EAM supports the work of maintenance organizations by conducting the planned maintenance actions to the assets of a plant. Examples of EAM include Maximo, Datastream 7i and

SAP Service and Asset management. The typical EAM functionality includes: asset management, work management, material management, procurement management, budget and planning, project management and reporting.

Business Intelligence (BI) systems are different IT systems that are used to collect, retrieve, integrate, store and analyse data and produce value-added information for supporting effective business strategy implementation. The purpose of BI systems is to produce information about changes in the business environment for strategic decision-making. BI often uses the so-called Key Performance Indicators (KPIs) to assess the present state of business and to prescribe a course of action. Examples of BI systems include Open-Source products like Pentaho and large commercial providers like SAP Business Information Warehouse, and Microsoft Analysis Services. The structure of a BI system is quite ambiguous but the functionality of BI generally includes the following: data warehouses (DW), data marts (DM), data extraction, storage and mining technologies, integration tools, query and reporting software.

DCS supports the work of human workers and automates part of the activities relating to the production processes in process industry (levels 0, 1, 2 in IEC [2003a]). Examples of DCS include metsoDNA, IndustrialIT System 800xA and Simatic. The functionality of a DCS maybe outlined to support the following activities: monitoring, predefined control tasks, disturbance control, information exchange, knowledge handling, development and learning.

6.3 IT requirements of decision-making

The business processes of MOM are management type of activities in which human decision-making has an essential role. Another important aspect of these activities is that they are performed by a group of people in a network of related activities. The decisions of decision-makers are dependent on the decisions of others. The requirements of the activities of MOM for decision-support may be outlined both from the perspective of decision-making in general and collaborative decision-making in particular. The requirements derived from these perspectives concern the functionality, data and knowledge provided and handled by the information systems. An additional viewpoint to the requirements is the architecture of the information systems of MOM. Information systems designed for decision-support share common elements in their architecture.

The information systems of MOM management need a set of functions in order to support the decision-making activities of their users. They need functionality to support different activities of decision-making as they appear in different activities of MOM. The required decision-support functions include situation assessment, development of decisions and execution and monitoring of actions. An interpretation of these requirements for decision-support in the context of MOM is presented in Table 6.1. The requirements also concern about the data and models handled in the information systems for MOM.

Table 6.1. Summary of the requirements of decision support in MOM.

Name	Explanation	Relevance
Support situation assessment	There should be functionality for collecting information and creating new information, which is useful for the decision-makers in their situation assessment activity. The information contains various types of data and knowledge.	This requirement is relevant to many situation assessment functions in DCS, CBM, MES, EAM and BI.
Support developing decisions	There should be functionality for creation, evaluation and selection of decision alternatives for various decision-making situations.	This requirement is relevant to many action planning functions in DCS, MES and EAM.
Support executing and monitoring actions	There should be functionality for execution of committed decisions for various types of decisions and monitoring the execution of these decisions.	This requirement is relevant to those action planning functions in DCS, MES and EAM, whose execution is performed or whose execution can be monitored via automation and information systems.

In order to support the collaborative decision-making activities of their users, the information systems of MOM need an additional set of functions. They need functionality to support different aspects of collaborative decision-making as they appear in MOM. The required functions include support for information exchange, and knowledge and business process management. An interpretation of these requirements for support of collaborative decision-making in the context of MOM is presented in Table 6.2. The requirements also concern the data and knowledge handled in the information systems for MOM.

Table 6.2. Summary of the requirements of collaborative decision support in MOM.

Name	Explanation	Relevance
Support information exchange	There should be functionality for exchanging information among decision-makers in a way that is useful in their decision-making activities.	This requirement is assumed to be relevant to many functions in DCS, MES, EAM and BI.
Support knowledge management	There should be functionality for sharing knowledge among decision-makers in a way that is useful for them in their decision-making activities.	This requirement is assumed to be relevant to at least some functions in DCS, MES, EAM and BI.
Support business process management	There should be functionality for the decision-makers to manage the business processes in which their decision-making takes place, in a way that is useful for the objectives of the business processes.	This requirement is relevant to many functions in MES and EAM.

In addition to the functional and data requirements, decision support has requirements also for the architecture of the information systems of MOM. The systems need models and administration functions for data, knowledge and decision-making logic. They also need mechanisms for collecting and communicating data and knowledge. Again, there is a need for integration among various systems. A summary of the IT architecture requirements in MOM is presented in Table 6.3.

Table 6.3. Summary of the requirements of IT architecture in MOM.

Name	Explanation	Relevance
Support data administration	There should be functionality to store and access various types of data that are useful for decision-makers in their situation assessment, action planning and collaborative decision-making activities.	This requirement is relevant to most (or all) functions in DCS, CBM, MES, EAM and BI.
Support knowledge administration	There should be functionality to store and access various types of knowledge that is useful for decision-makers in their situation assessment, action planning and collaborative decision-making activities.	This requirement is relevant to those functions in DCS, MES, EAM and BI, where the situation assessment, action planning and organizational decision-making activities of the decision-makers can be facilitated with knowledge stored in information systems.
Support model administration	There should be functionality to store and access various models for data processing which are useful for decision-makers in their situation assessment and action planning activities.	This requirement is relevant to those functions in DCS, MES, EAM and BI, where models of data processing are used.
Support integration between systems	There should be functionality to transfer data and knowledge between systems and means for invoking functionality of other systems to the extent that is required by the previously presented requirements.	This requirement is relevant to DCS, CBM, MES, EAM and BI. It is also relevant to ERP as a system with which the previous systems might be needed to be integrated.

6.4 Applicable new information technologies

The new information technologies that are assumed to have an impact to the decision-support capabilities of the information systems for MOM in the future include SOA, Semantic Web technologies, OPC UA and MOM-related standards. Whereas the first two of these are part of general information technology, the latter two are specific to MOM. The basic aspects of these technologies are described in this section.

Service-Oriented Architecture (SOA) (Erl 2005) is a new architecture model for distributed software systems targeting towards better alignment of business processes and services with their software implementations. The basic elements of the SOA model are software services that correspond to self-contained business functions and business processes. The basic units of SOA applications are service components that can be simple or complex and that can be composed of other services. This kind of nested structure of services is a fundamental feature of SOA. One dimension often presented is a distinction of services based on their functional scope of business related responsibilities as illustrated in Figure 6.1.

The SOA approach is a style of programming that is independent of implementation technology and programming language used. However, the realization of SOA principles has been made possible through several open standards and technologies that support interoperability of services. For instance, the following technologies and standards are included in the SOA foundation: XML-technology and standards, several Internet related technologies, Web Service technologies, WS-I and WS-* standards, Business Process Execution Language (BPEL) specification and Service Component Architecture (SCA) specification.

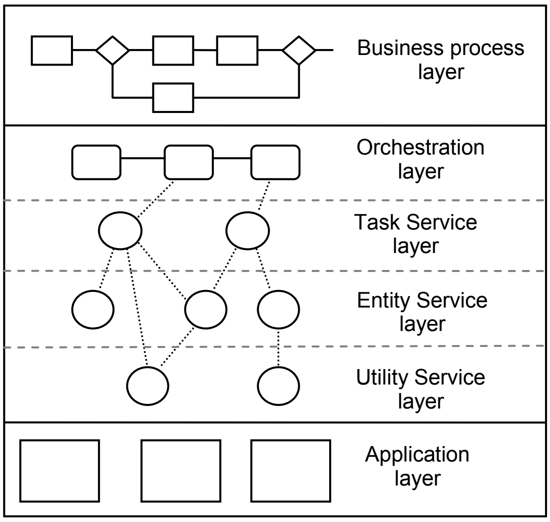


Figure 6.1. Layered SOA model and service categorization.

OPC Foundation has released a new interoperability standard, OPC Unified Architecture (OPC UA) (OPC Foundation 2006), especially for the process automation area. It provides a more unified and integrated way of accessing current data, historical data, alarms and events from automation systems and devices than the earlier OPC specification. OPC UA consists of three conceptual parts: communication services, address space and information models. All the functionality of the OPC UA is implemented using SOA. The services can be implemented ether using web services or the native OPC UA binary protocol. The OPC UA Address space meta-model allows high level information models to be created in an extendable way (see Figure 6.2). Information model standardizes only a general set of information elements and base types that are application area independent. The idea is that different application area specific and platform specific information models can be extended by vendors and organizations.

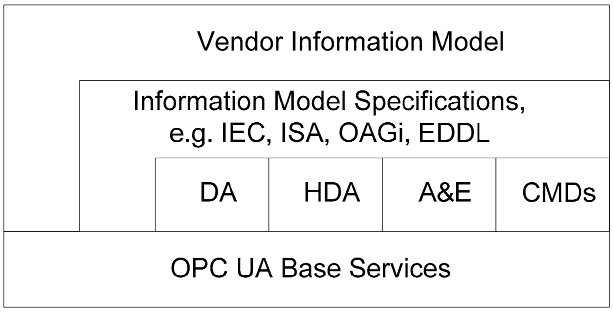


Figure 6.2. Layered information model of OPC UA.

The purpose of the ISA-95 standard (aka IEC 62264) (IEC 2003a) is "to create a standard that will define the interface between control functions and other enterprise functions based upon the Purdue Reference Model for CIM (hierarchical form) as published by ISA" (ISA-95 2001). Initially only the interface between MOM and ERP was considered. Later also interfaces within the activities of the MOM have been added to the specifications. ISA-95 consists of activity, object and transaction models. The models are intended to be used to determine which information has to be exchanged between systems for sales, finance and logistics and systems for production, maintenance and quality. The information is represented with UML models, which are intended to be the basis for the development of standard interfaces between ERP and MES systems.

In addition to ISA-95 there are also other standards relevant to MOM, e.g. OSA-EAI (Open System Architecture for Enterprise Application Integration) in the field of maintenance operations management and EDDL (Electronic Device Description Language) (IEC 2003b) and FDT (Field Device Tool) (FDT Group 2006) for device information management. OSA-EAI (MIMOSA 2006) is an architecture definition by MIMOSA (Machinery Information Management Open Systems Alliance). The main goal of OSA-EAI specification is to allow information integration and interconnection of information systems related to asset lifecycle management to enable collaborative maintenance networks to be built. EDDL and FDT define a language for describing field device configurations and an interface for accessing data about field devices. They are currently being being integrated with OPC UA through a specification called FDI (Field Device Integration).

Semantic Web technologies provide a new approach for managing information by raising the level of information processing towards conceptual and logical levels (Grigoris and van Harmelen 2004). The foundation of Semantic Web technologies is in formal conceptual models, ontologies that are machine exchangeable, readable and interpretable at logical level. The Semantic Web technologies are commonly considered enabling technologies that can be applied in several information processing areas including applications like semantic search and reasoning, unstructured information processing, information integration and more dynamic SOA applications based on so-called Semantic Web services.

Semantic web technology is based on standards that provide a basis for representing and using ontologies. The World Wide Web Consortium (W3C) has defined many important ontology language (RDF(S), OWL), ontology query language (RDQL, SparQL, OWLQL) and logic rule language (SWRL) specifications based on XML technology standards, which enable interoperability of ontology models and development of many generic tools and components (see Figure 6.3). In order to enable automatic semantic level processing of information, it must be in an ontology form or be extended with metadata annotations based on concepts from domain ontologies. A metadata repository with its domain ontology comprise a knowledge base for semantic queries, logical reasoning and finally for semantic information integration with other local knowledge bases.

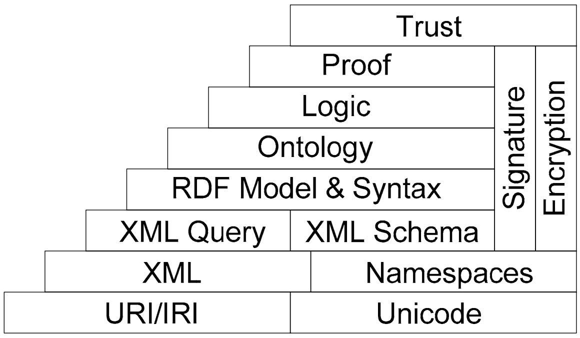


Figure 6.3. Semantic Web technology stack.

6.5 IT architecture for decision-support

It is expected that the previously presented technologies are likely to be applied to the information systems of MOM in the future in one way or another. This development is already ongoing. Several functionalities of legacy systems are wrapped with web service interfaces enabling them to be information service providers for service oriented applications. The newest versions of some ERP and MES systems already support web service based interoperability. Furthermore, large information system vendors sell information servers, integration servers and other middleware products whose architecture is based on Enterprise Service Bus concept that is the backbone for service life-cycle management. However, if these technologies are aimed for enhanced decision-support capabilities, then the requirements of decision-support should be noted in their usage.

A proposal for a future IT architecture for information systems of MOM may be outlined based on current information systems and adoption of SOA, OPC UA and other standards and Semantic Web technologies. The most essential differences between this architecture and the current IT architecture would be more explicit support for various requirements of decision-making and an increased level of integration among the separate information systems. The proposal for the future IT architecture for information systems of MOM is illustrated in Figure 6.4.

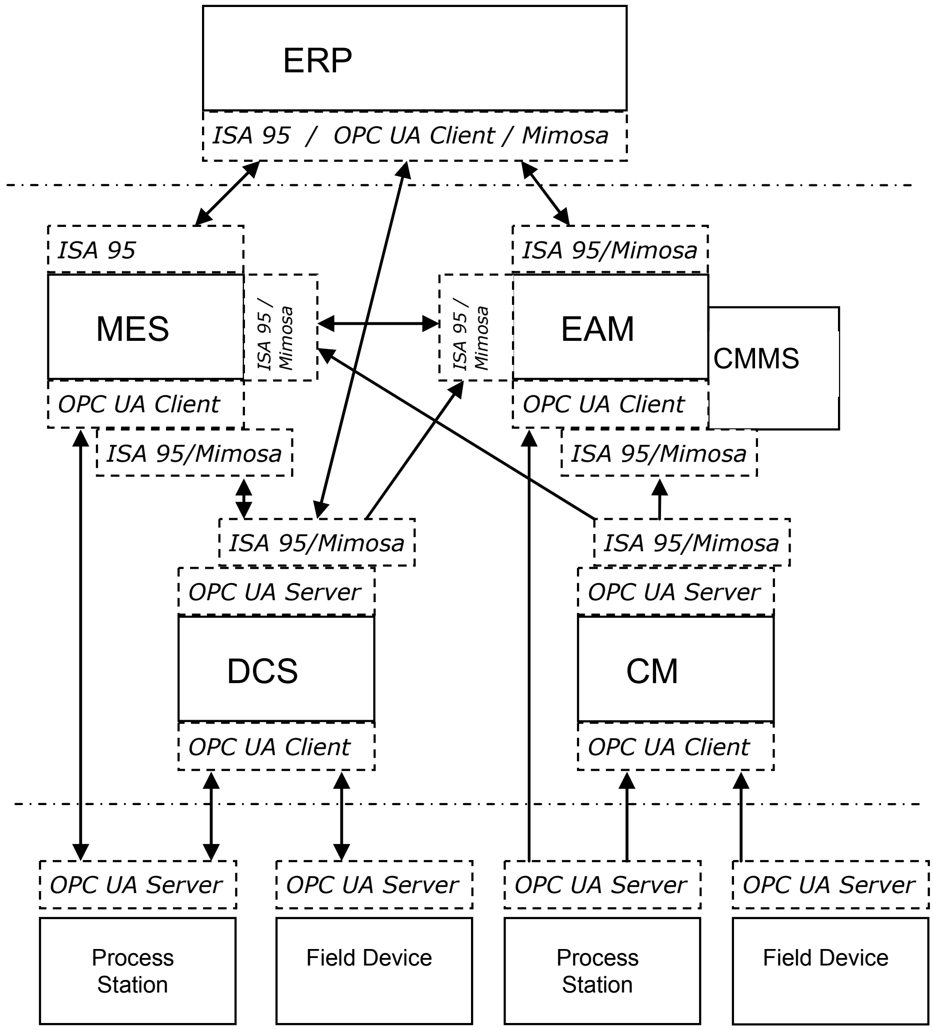


Figure 6.4. Possible future IT architecture for operational decision-making in the process industry with enhanced decision-support capabilities.

The role of SOA in the architecture is to enable increased functional integration among the separate information systems of MOM. There are several requirements of decision-support that can be argued to indicate the applicability of SOA. First, it seems likely that at least part of the decision-support functions will require combination of functionality from separate information systems. SOA could make implementation of such inter-system functionality less laborious. Second, support for collaborative processes involving several decision-makers in a common business process suggest also a need for a combination of functionality in several information systems and a need to manage the collaborative process. This kind of needs seems to fit the SOA-model quite well. Third, the requirement of data and knowledge collection and transfer for decision-support purposes could take advantage of common interface standards of SOA-related technologies. The adoption of SOA and its related technologies is already a part of commercial information systems development. However, this technology is still quite new and going through heavy development.

The role of the MOM-related standards is to enhance information integration among the information systems of MOM. The primary requirement of decision-support that suggests the adoption of the standards is the need for data transfer among the various information systems of MOM. The application of the standards is relatively straightforward. The interfaces defined in them would be implemented into commercial information systems and the data and transaction models used when integrating them. The question concerning the utility of these standards is the extent to which they will be adopted by the vendors of various information systems. However, the standards are gradually being developed and parts of them are already being used in new integration projects.

The role of the Semantic Web technologies is to be the next development step after the adoption of the previous technologies. The information integration between the information systems of MOM might be further enhanced if XML Schemas used in standards are upgraded to RDF or OWL. However, how this should be done is currently a research topic rather than tested technology. Again, SOA-based integration could possibly be enhanced further with the adoption of semantic web services. How this should be done and if the decision-making requirements really need this are also currently research questions.

References

Erl, T. 2005. Service-Oriented Architecture: Concepts, Technology and Design. Prentice-Hall.

FDT Group. 2006. FDT Technical Description. FDT Group Publication.

Grigoris, A. and van Harmelen, F. 2004. A Semantic Web Primer. MIT Press.

IEC. 2003a. Enterprise – Control System Integration, Part 1: Models and Terminology. IEC Standard 62264-1.

IEC. 2003b. Function Blocks (FB) for Process Control, Part 2: Specification of FB Concept and Electronic Device Description Language (EDDL). IEC Standard 61804-2.

MIMOSA. 2006. Open System Architecture for Enterprise Application Integration (OSA-EAI). MIMOSA Specification. Version 3.0.

OPC Foundation. 2006. OPC Unified Architecture, Part 1: Concepts. OPC Foundation Specification. Version 1.00.

7. Use cases for operational decision support system

By Miika Nurminen, Panu Suominen, Sami Äyrämö and Tommi Kärkkäinen
University of Jyväskylä

7.1 Introduction

The task of decision making can be divided into three steps (Simon 1976): (1) the identification and listing of all the alternatives; (2) the determination of all the consequences resulting from each of the alternatives; and (3) the comparison of the accuracy and efficiency of each of these sets of consequences. Simon (1965) refers to the first of these as *intelligence* (in a "military" sense), the second as *design*, and the third as *choice.* Simon's division combines the organizational (descriptive, what decisions could and should be made) and technical (normative, how you should make the decision) views on decision making. The OODA Loop is another decision making model created by military strategist John Boyd (2007). The model is meant for organizations that undergo continuous interaction with their environment. The OODA loop consists of four overlapping and interacting processes, namely *observe*, *orient*, *decide,* and *act*, that are in continuous operation during the interaction.

During the consortium project we have shared a detailed documentation on the specification of generic operational decision support system (ODSS) which is based on statistical decision theory (SDT). This generic user requirements (GUR) document, as given in Appendix A, is based on ideas similar to those of Simon and further elaborated by (Jokinen et al. 2008), providing a comprehensive checklist for the development of any system supporting operative decision making based on SDT. However, as pointed out by Simon, organization-wide decision making is more than just a software realization of one decision support technique, so that an organization-wide DSS should be based on abstraction levels (layered architecture) separating decision task selection and actual decision making support in a modular way. From the enterprise architecture point of view (see e.g., Kilpeläinen 2007 and articles therein), a comprehensive description should initially focus on *contextual and conceptual* enterprise levels instead of physical or detailed representations in light of the classical Zachman's framework (Zachman 1987).

Moreover, the GUR description in Appendix A is conceptually rather "loaded" i.e. it contains a significant amount of different concepts with ambiguous meanings (e.g. referring to SDT elements). Hence, in this chapter, we augment the GUR specification with *business use case -like descriptions* (Cockburn 1997). Actually it is quite common (see

Bittner and Spence 2002) that functional specification of a system that is strongly based on one particular realization technique can yield a large descriptional bias.

We present the revised DSS specification in the form of use cases to support creation of a conceptual model. The use cases and the resulting conceptual model can be used to set fixed and common terms among the DSS stakeholders. The use cases, the conceptual model, and the reference models for decision support systems can be used to analyze the possible structure and abstraction layers of the general operational decision system being investigated. Further, the stereotypes and concepts discovered from use cases form a base for a domain-specific ontology that can be applied for information integration and automated reasoning about decision support systems.

The contents of this chapter are as follows: first, we provide an introduction to previous related research. Next, we present the use case specification for a generic ODSS. The use case specification is used to generate an entity model that describes the domain for decision support systems. Finally, the chapter is concluded.

7.2 Preliminaries

This section provides a short introduction to not yet covered related research from organizational, information systems, human decision making, and system specification perspectives.

7.2.1 The degree of digitalization and its impact on information systems

The amount, degree and form of communication used in organizations should be taken into account when designing decision support systems. With the current trends of digitalization and the convergence of networks, the amount of available information is higher than ever. Thus, defining and gathering necessary information is a crucial step in realizing decision support.

The digitalization trend has generated new problems and added to the impact of existing ones, such as information overload. The ease of information distribution, for example by overdistributing or forwarding mail to many people, can impair organizational communication by overloading the persons receiving the data with irrelevant or secondary information (Kilpeläinen 2007).

Despite the increased digitalization of documents, organizational information will never be available in its entirety for automated processing by decision support systems. In (Kilpeläinen 2007), organizational communication from three industrial and academic organizations was analyzed. Overall, it seems that digital documents account for about 40–55% of total communication (depending of the measures used), leaving out analog representations (e.g. paper) and other communication (e.g. face-to-face, phone). Since some of the analog documents are produced digitally despite the medium used (e.g. printing documents), the actual amount of digital communication might be higher, but still a notable part of communication takes place outside the information systems.

Even if both digital documents and other communication forms are considered, tacit knowledge can not be directly accessed by a decision support system, even though it may have a pivotal role in decision making compared to official documentation. In principle, this can be alleviated by expressing tacit knowledge explicitly to become part of the organizational information resource, but in practice both measuring and acquiring tacit knowledge can be difficult and time-consuming. Therefore, one should note that any information system can have direct access only to a fraction of the total knowledge present in an organization.

7.2.2 On decision support systems

Decisions can be seen as a way of addressing a problem. All decisions contain some kind of procedure or chain of reasoning as to how the problem should be solved. If not, decision degenerates to merely guessing. However, the level to which the procedure can be automated or the so called structuredness of the problem can vary greatly. Basically one can define three categories based on the structure: structured, semistructured, and unstructured (Gorry and Scott-Morton 1971).

For structured problems there exists a known procedure (e.g. standard operating procedures and processes, operations research, electronic data processing and heuristics) to find the best or a good enough solution (Simon 1965). Semistructured problems have some parts that are procedurally solvable and others that are not. Unstructured decisions consist of seeking answers to problems that have no known and robust method for solving them. For example, planning for research and development is highly unstructured problem while locating a warehouse is a structured one.

To help solve these problems decision support systems can be employed. The DSS is designed to support the user in making a certain decision. Usually this is achieved through modelling a subset of the real environment and analysing possible outcomes of decision candidates. Sometimes just simple calculations are enough. DSS covers a broad range of applications from simple spreadsheets to sophisticated artificial intelligence systems – all having in common the goal to ease solving the problem they are designed to help with.

Turban et al. (2004) describe three essential subsystems of DSS (see Figure 7.1): data management, model management, and user interface (UI). Hence, DSS is constructed from data, ways to manipulate them, and an interface for the user to interact with the system. Additionally there might be a knowledge management system that provides intelligence for the system. As is often the case with general concepts, DSS subsystems are loosely defined.

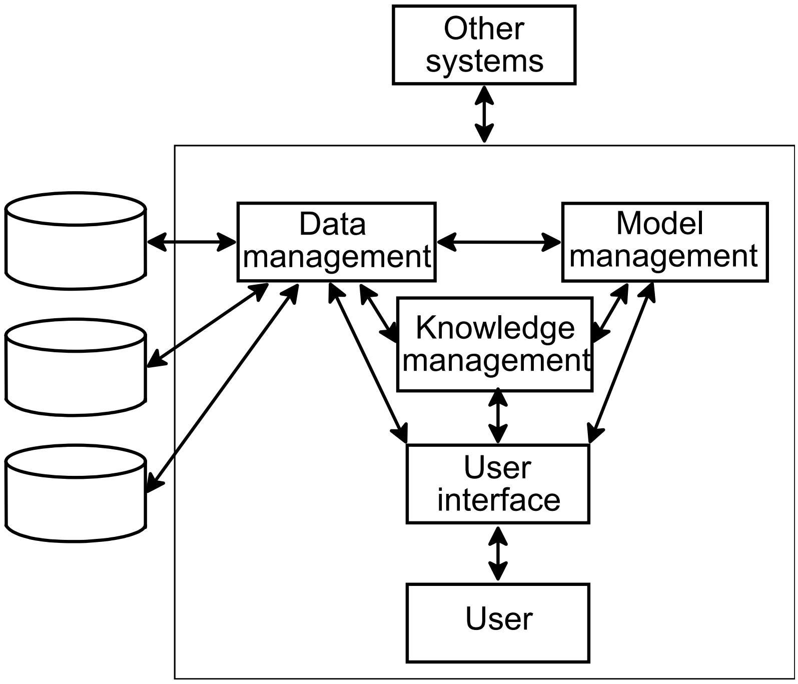


Figure 7.1. The general framework of decision support systems (Turban et al. 2004).

- **Data Management**. To make rational decisions some kind of (relevant) information is needed. Handling this data is done through a data management system. It is often based on some kind of database management system. In a corporate management environment the system could be connected to the data warehouse of the corporation to provide relevant information.

- **Model Management**. Models are routines that are made to provide some kind of analysis capability in DSS. They can be complicated simulations or just simple calculations that use information stored by the data management system. The model management system provides means to create, modify, and run the models. This requires the subsystem to be able to handle models similarly to data. Same database backend might be used also for model storing.

- **User Interface**. User interface enables handling models and information to support given decision task. Because of the close relation to human cognition user interface should be considered carefully to support the decision task and to minimize errors caused by misunderstanding data and analysis.

- **Knowledge Management**. Many problems require expertise to solve them and the results from an analysis can be difficult to interpret. In DSS this can be provided with a knowledge management subsystem. It is basically a collection of methods derived from artificial intelligence research that enable classification and heuristic evaluation of results or automatic problem solving.

7.2.3 Cognitive biases and decision making

Arnott (2006) claims that although influences of DSS on decision performance are often disappointing, focusing on decision-making and tailored support can lead to successful systems. Arnott perceives DSS to be fundamentally about decision making and thus a DSS analyst should have knowledge about human decision processes and how to improve them.

It seems likely that without knowledge of human behaviour the system will fail in helping to make the right decisions. For example, even if the system could give accurate answers for any given problem, people are not likely to follow them if they don't feel they are in control and understand the chain of reasoning behind the answers. This is because people are likely to overestimate their chance of success when they are in control (Mann 2002) even if they are not equipped for the given task.

The decisions made can vary from the most rational choice. Predictable deviations from rationality are called cognitive biases. Arnott classifies 37 biases into categories of memory, statistical, confidence, adjustment, presentation, and situation presented here briefly.

- **Memory biases** (*hindsight, imaginability, recall, search, similarity, testimony*) are mostly due to the fact that people remember and recall familiar events more easily than others. Such a human judgment then easily yields an incorrect estimation of possibilities. To help users cope with these tendencies DSS should provide information from the past and provide statistical information. User interface should take good care that figures are represented in a neutral way. Also every view should contain enough accurate information to deal with the current task, thus avoiding overloading users' short term memory.

- **Confidence biases** (*completeness, control, confirmation, desire, overconfidence, redundancy, selectivity, success, test*) arise mostly because of a decision maker's overconfidence in his/her skills. When underestimating the problem people tend to choose the first complete-appearing solution without considering alternatives. People are likely to look for confirming evidence while ignoring the search for disconfirming information. To address these problems DSS should show alternatives and present the uncertainty of information. Structuring should also reveal the difficulty of decisions. DSS should keep a record of the decisions made, enabling users to evaluate how successful they have been.

- People tend to be lazy and do not adjust enough to a change of environment. This kind of ignorance of potentially significant new data is categorised under **adjustment biases** (*anchoring and adjustment, conservatism, reference, regression*). DSS using up-to-date models based on recent data (on-line adaptation) provides the most reliable adjustment to the task at hand by the decision maker.

- The way information is represented can make a big difference. Scale differences between graphs can lead to wrong conclusions. First or last items in the list can be overweighted and so on. Problems arising from **presentation biases** (*framing, linear, mode, order, scale*) can be avoided by using consistent user interfaces with unified views.

- **Situation biases** (*attenuation, complexity, escalation, habit, inconsistency, rule*) include the human tendency to follow a previous unsatisfactory course of action, choosing an alternative only because it was used before. People are also eager to simplify the situation by ignoring or significantly discounting the level of uncertainty. DSS needs appropriate structuring (sequencing) of the decision tasks. Also history databases of decisions made earlier and their consequences should be stored and (re)utilized.

- **Statistical biases** (*base rate, chance, conjunction, correlation, disjunction, sample, subset*) result from misinterpretation of data that should be treated as random variables. Please refer to Chapter 2 for a discussion on compensation and avoidance.

Debiasing or compensating for the erroneous behaviour of the user should be considered when designing DSS, because these biases might alter the decision significantly. Alternatives to help the user overcome these shortcomings can vary from carefully considered user interface, statistical data, and representation of the probabilities, as well as just informing the user of common mistakes that people are likely to make in the current situation. If the problem can be structured this will help with these issues because the program is more able to follow the actions of the user. From a design point of view, methods for following users' behaviour should be implemented to track the success of debiasing strategies.

7.2.4 Use cases for system requirements

Use cases are a popular method used in the requirements elicitation phase of a software development process. Requirements elicitation involves acquiring information about SuD (System-under-Development). To get a complete picture of the requirements, they are considered with different stakeholders of the SuD. In requirements engineering lingo, a stakeholder is someone with an interest in the future system, e.g. a user, administrator, maintainer, etc. Use cases focus on describing the use of SuD as a part of workflows and business processes related to relevant stakeholders.

A use case is a description of the desired functionality of SuD in a given situation. According to Cockburn (2000), “A use case captures a contract between the stakeholders of a system about its behavior”. A use case provides an important context for the distinct functional requirements, how they are connected, the situations they are relevant in, and the related trigger conditions. The level of detail of a use case varies widely and can be adjusted on a per-project basis. Also, the details are usually added in breadth-first, starting with the names of all the use cases and proceeding as far into detail as needed, usually by assigning attributes such as priority, success guarantees, etc.

Use cases do not describe the so-called non-functional requirements of SuD. These include measurable conditions and constraints related to e.g. performance, security, data requirements (Lauesen 2002), user interfaces, etc. Thus, use cases are not sufficient means to document all the requirements of a software system. Also, use cases are not well suited for all systems, e.g. reactive systems which constantly observe the surrounding environment and act accordingly (embedded real-time systems) (Jackson 2001).

Use cases have structurally much in common with business processes and workflow specifications, although the semantics, detail, and scope differ. Use cases usually focus on the interactions between the user and the system, whereas workflows and business process models tend to describe more general, higher-level activities – often omitting detail in the process models. For example, Sharp and Dermott (2001) utilize use cases to elicit system requirements for specific steps in a process model. However, since a business process can be defined as a specific ordering of work activities across time and place with a beginning and an end containing clearly defined inputs and outputs (Davenport 1993), at a syntactic level both use cases and business processes can be modelled with a graph structure. Furthermore, Cockburn points out that any system that offers a set of services for outside actors while protecting the interests of the other stakeholders can be described with use cases. This includes business systems.

Writing style, conventions, and consistent terminology are essential when considering the understandability of the use cases and the effectiveness of automated postprocessing of the models. Postprocessing techniques include data mining (Nurminen et al. 2005) and natural language processing (Kärkkäinen et al. 2008). This can be a challenging task in itself, because different people tend to produce different models even given the same domain (Soffer & Hadar 2003). To alleviate this, use cases presented in the next section were written in an iterative way with multiple reviews.

7.3 DSS specification

Next, a use case based specification of a generic (hypothetical) operational decision support system is presented. The GURs in Appendix A were the starting point of the specification but we present revised use cases with hierarchical layers and somewhat simplified writing conventions to ease the understanding of key functionality. Arnott's biases (2006) are also accounted for in the specification. The purpose of the revised use cases is to provide easily understandable material for communicating about System under Development without loss of accuracy.

The use cases presented establish a connection between the organizational level decisions of which tasks are to be handled by DSS, and the actual decision making with DSS. In this way, the two main foundations of operational decision making, i.e. technical support for decision making in the form of a formal decision making model (normative decision making) and the organizational thinking (descriptive decision making) point of view are both captured. To this end, the specification of DSS is the main concern here, but to have such a system in active use as part of everyday organizational operations requires resources and processes for systems' maintenance – the part (i.e. the lack) of the software/information system lifecycle which often causes the bad user experience.

7.3.1 Use case model

Our manual inspection of generic user requirements leads to the basic structure for SuD presented in Figure 7.2. The process starts with the need for the decision. This need can be triggered automatically by the system or specified manually by the user. If user sees the need for the decision there might not be a proper model and the decision task has to be modeled before any further action. After the model exists the DSS is able to generate a decision proposal. In some cases this is not possible and the user is able to work with the data, models, and structures that are available without the proposal (semistructured decision problem) (Gorry & Scott-Morton 1971). In the decision making process the decision maker is able to change which data are used, and possibly the parameters in the model to support the evaluation of the alternatives.

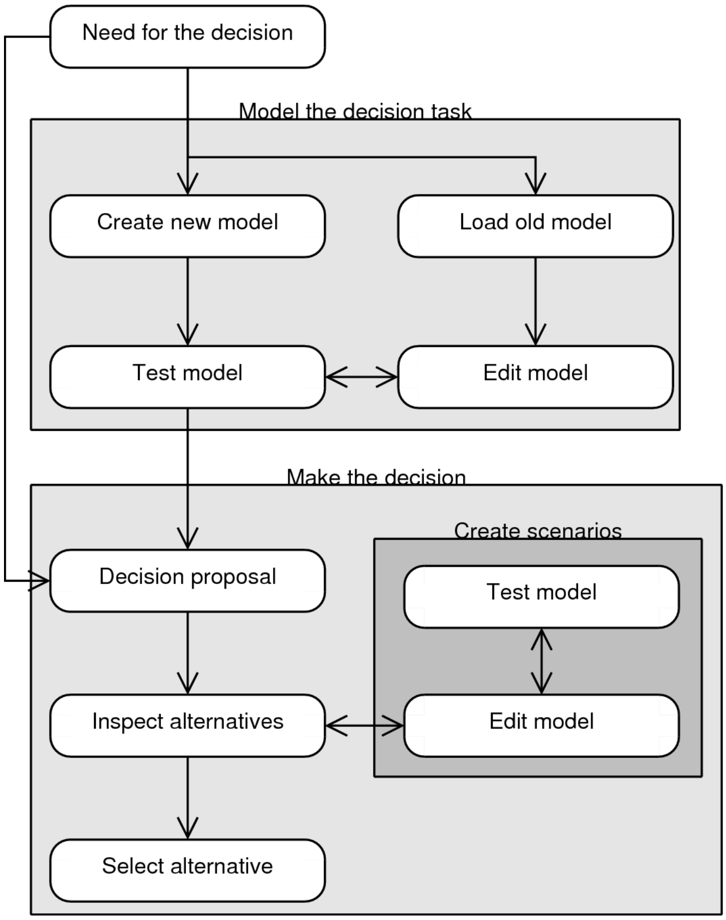


Figure 7.2. Basic structure and expected workflow for a decision support system.

The program main flow scenario in Figure 7.2 does not take into account the group decisions and some configuration steps that precede the usage of DSS. For example, defining data available to DSS is a requirement that is missing from this flow representation (GUR-2.1.2b in Appendix A). The steps for a single decision maker are considered in use cases and group working can be represented as variations (e.g. differing in actors or certain steps) to original scenarios. While these variations are important when a real system is developed, they make little difference when building a conceptual model because the variations by definition share many of the main steps of the use case.

The use cases presented here are generic. The actual configuration and location of systems and databases depend on the target organization. For example, if a workflow system with well-defined process descriptions is already present, it may provide detailed information about potential decision tasks to DSS. In addition, the evaluation of consequences depends essentially on the nature of a decision task. Some decisions have an instant, measurable outcome that can be detected automatically (e.g. on-line quality measurements of the end product in a product line), but most decisions are of a more abstract nature (e.g. financial, strategic decisions) that cannot be determined or even executed in a short time period.

Roles

The following generic roles are applied in the use case descriptions. Depending on the organization and the position of a decision maker, it is possible that more than one role is performed by a single person.

- **System Expert** is responsible for the DSS maintenance and configuration, data connections, software/method extensions and updates. This role presumes extensive technical skills in information technology, software engineering, and to some extent, in knowledge discovery, data mining/analysis, and statistics. The tasks of the System Expert might be partly or fully outsourced.

- **Decision Configurator** is responsible for the availability and storage of necessary data sources. He/she analyzes the information sources/flows in the organization and responds to the data requests from the Method Expert and/or the Decision Maker. The role presumes extensive skills in information technology, data engineering, and knowledge management. To some extent, skills in software engineering might be also needed.

- **Method Expert (Analyst)** is responsible for applying the computational and statistical methods of DSS to the target datasets. He/she has extensive knowledge in selection, usage and configuration of the methods. This role presumes extensive skills and deep understanding in optimization, simulation, data mining/analysis, statistics (incl. SDT), and other related methods. The Method Expert must be able to communicate about technical issues with the System Expert/Decision Configurator and, moreover, with the Decision Maker about the meaning of the results and representations. The tasks of Method Expert might be partly or fully outsourced.

- **Decision Maker** is an experienced domain specialist who makes decisions and is usually responsible for the outcomes. The Decision Maker is not expected to have detailed technical-level understanding of decision support methods or models, but based on domain experience he/she can evaluate the impact of different decision alternatives provided by domain and system experts, or the DSS.

- **DSS Configuration Team** combines the appropriate level of management and selected experts representing the aforementioned roles. The team maintains the decision support system by analyzing the need for supporting new decision tasks, decision making principles, methods, models, and pre-configuring decision tasks templates that guide predefined decision making tasks.

Information systems

DSS contains or interfaces with following libraries, databases, and other information systems:

- **Method Library** contains decision support techniques, such as large-scale data mining/analysis (clustering, neural networks, association rules etc.), SDT, (multiobjective) optimization, dimension reduction methods, and visual representation techniques. New methods can be added to the library by the System Expert. Utilization of the methods requires the tuning of parameters (distribution parameters for state estimation model, prototypes for clustering model etc.) or retrieving them from the Decision History Database, and the testing (validity, sensitivity etc.) of parameters. The Method Library is roughly equivalent to the Knowledge Management Subsystem in Turban's framework.

- **Decision History Database** contains data about previous decision support processes and analysis steps that are supported by the system. These data include the relevant information about decision making cases (date of problem, problem description, short-/long-term consequences etc.), analyzed data sources, operational tasks and method selections, input parameters (optional) of the applied methods, and obtained models (alternatives) with parameters. This database enables repetition of the previous decision support cases for new data and parameters. The consequences of the accomplished actions must be gathered for reusing the cases. Non-direct consequences are reported to the database later by the Decision Configurator or the Decision Maker. Direct outcomes are collected into the database automatically if possible.

- **Decision Template Database** consists of predefined decision making tasks that can be used to guide the decision support process. Each template defines the method selections, appropriate parameter settings, perhaps pre-adjusted models, visual representations, and informative descriptions. The templates are defined by the DSS configuration team. The templates are entered into the database by the Decision Configurator. The Decision Template Database is equivalent to Turban's Model Management Subsystem.

- **Organizational Data Sources** are information systems and databases that are used in the day-to-day operation of the enterprise. These provide the input data for the decision support system for analysis. The System Expert is responsible for providing connections to data sources. If the data from Organizational Data Sources is gathered to a permanent data warehouse to be used by DSS, this would be equivalent to Turban's Data Management Subsystem. However, ad-hoc usage without a dedicated data warehouse should also be possible, depending on the analysis methods used.

Conceptual stereotypes

The concept glossary (i.e. informal definitions for concepts) is needed to establish a joint language between stakeholders (managers, developers, users etc. related to DSS) (Bittner & Spence 2002). We base the glossary on use cases thus providing not only documentation about the existence of a concept but also its context of use. Moreover, attaching a stereotype to each concept creates a classification of them, supporting the critical transfer from domain analysis into system development. The introduction of stereotypes also clarifies the structuring of use case flow, because joint concepts related to system usage and its realization are tagged (Cockburn 2000). Moreover, there is no need to prolong the use case main scenario by repeating the user action and system response in connection with the same concepts (Wirfs-Brock 1993). We recommend that for a shared information transfer step between user and system ("Actor creates X" → "System stores X") the *use* case should be described from user's (usage) perspective only ("Actor creates X", tag X as persistent data stored by the system).

Table 7.1 contains definitions of the stereotypes that were used to classify the concepts. DecisionModelElement is specific to Decision Support Systems domain; other stereotypes are domain-independent.

Table 7.1. Definitions of the stereotypes that were used to classify the concepts.

Stereotype	**Description**
Action	Functionality needed by SuD
Data	Persistent information used internally by SuD
Database	Database to be managed by SuD
Document	Document to be produced by SuD or a report that SuD must generate to a user
ExternalAction	An external action that SuD must take into account
ExternalData	Data stored by other systems available and necessary for SuD
ExternalRole	External human or device that SuD must communicate with
Metadata	Data about data
Process	A specific ordering of work activities across time and place with a beginning and an end containing inputs and outputs
Role	Stakeholder role (the classification of a set of stakeholder representatives who share the same roles and responsibilities with respect to the project)
Selection	A particular choice related to a particular UserElement
System	SuD or other information system related to use case
UserElement	An element representing the interaction interface between a user role and SuD
DecisionModelElement	General entity related to the decision making model

Use cases

The overall structure and primary actors of the use cases are presented in Figure 7.3. Use case 1, *Perform Organizational Configuration and Decision Making Processes* presents the general process of utilizing decision support system in an organization and includes other use cases that are expected to be performed in an iterative way: Decision Tasks must be modeled before Decision Makers can use the system to make decisions. Finally, the Decision Maker can propose configuration change requests that can be implemented by the Configuration Team in the ongoing process of maintaining DSS.

Use case steps and related concepts are presented in Tables 7.2–7.9. Each use case may include notes that provide details to individual use case steps and references to related chapters. Numbers in parentheses denote links to another use case.

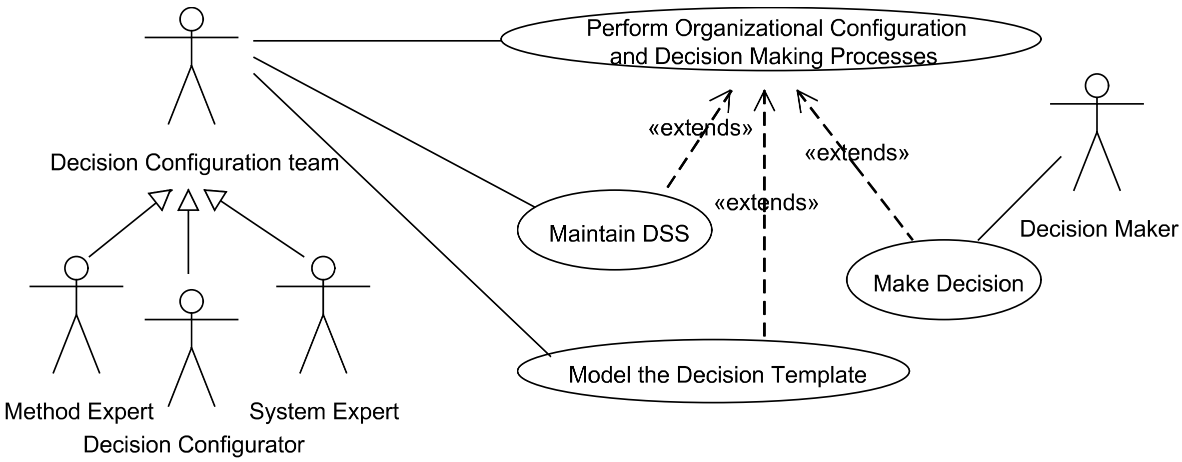


Figure 7.3. Use cases for DSS.

Table 7.2. Use case 1 – Perform Organizational Configuration and Decision Making Processes.

Id	Description	Concepts: Stereotype
1	DSS Configuration Team defines the set of organizational Decision Tasks to be supported by DSS and maintained by Decision Template Database.	DSS Configuration Team: Role Decision Task: UserElement DSS: System Decision Template Database: Database
2	DSS Configuration Team defines Necessary and Available Information for Decision Tasks.	Necessary Information: Data Available Information: ExternalData
3	DSS Configuration Team defines the set of available Decision Support Techniques to Method Library.	Decision Support Technique: DecisionModelElement Method Library: System
4	Method Expert documents the Decision Support Techniques to Method Library.	Method Expert: Role
5	DSS Configuration Team defines content of Decision History Database.	Decision History Database: Database
6	Decision Configurator Team models the Decision Templates (2) which are supported.	Decision Template: DecisionModelElement
7	Decision Maker makes Decisions (3) supported by DSS.	Decision Maker: Role Decision: Action
8	DSS Configuration Team maintains DSS (4) based on Configuration Change Requests.	Configuration Change Request: Document

Table 7.3. Notes for use case 1.

Step	Note
1	Selection of Decision Tasks to be supported by DSS can be based on e.g. critical task analysis (see Chapter 5), available data, existing knowledge sharing technology (e.g. digital diary between shifts) or process simulation models, the criticality of a decision concerning operative actions, the decision maker's capabilities and motivation etc. (cf. organizational thinking in Chapter 3).
2	Available Information refers to relevant (secondary) digital information, e.g. measurement data, laboratory analysis results, performance summaries, O&M reports etc. stored by existing systems. For limitations, see Section 7.2.1.
3	Possible techniques are described in Chapters 2 and 3 and references therein.
4	Some expertise is needed e.g. to introduce SDT portfolio for organizational unit management, as proposed in Chapter 2.
5	Here meta-information and comments can be attached to a decision to be stored along with reference to the applied decision support model.

Table 7.4. Use case 2 – Model the Decision Template.

id	Description	Concepts: Stereotype
1	DSS Configuration Team derives a generic Decision Task from past decision support cases.	DSS Configuration Team: Role Decision Task: UserElement
2	Decision Configurator checks the availability of relevant internal/external task-specific data.	Decision Configurator: Role
3	Method Expert attaches the Decision Support Technique suitable for the Decision Task to the Decision Model and notifies about necessary but missing connections from DSS to Organizational Data Sources in DSS.	Method Expert: Role Decision Support Technique: DecisionModelElement Decision Model: UserElement Organizational Data Source: Database DSS: System
4	System Expert creates the necessary but missing connections to Organizational Data Sources.	System Expert: Role
5	Decision Configurator specifies Trigger Condition for recognizing the need to perform the Decision Task.	Trigger Condition: Action
6	Method Expert defines the suggestive Decision Model Parameters for model building (distribution models, visual representations etc.) and inputs the parameters into the Method Library.	Decision Model Parameter: DecisionModelElement Method Library: System
7	Decision Configurator describes Decision Objectives and Decision Alternatives.	Decision Objective: DecisionModelElement Decision Alternative: DecisionModelElement
8	Decision Configurator attaches a structural Decision Making Process (i.e. phases or stages) yielding to a Decision Proposal for each Decision Task and stores it in the Decision Template Database.	Decision Making Process: Process Decision Proposal: UserElement Decision Template Database: Database
9	System Expert runs test cases (e.g., using earlier decision support cases) and reports the results to the Method Expert.	
10	Decision Configurator documents the elements of the Decision Model and its relation to Decision Support Technique in Concept Documentation and stores the Decision Model, its Concept Documentation, its testing and version history in the Decision Template Database.	Concept Documentation: Document

Table 7.5. Notes for use case 2.

Step	Note
	Steps 5–8 can occur many times in any order.
3	Method Expert might decide to load an existing model to be the base of the model creation. Decision Model includes relevant data for the Decision Task to be used with the Decision Support Technique.
5	Triggers for performing Decision Tasks are elaborated in Chapter 2.
6	In the case of data clustering (described in Section 3.1) as a decision support technique, this step means the estimation of clusters and prototypes comprising the decision model with chosen data. Uncertainty of the obtained clusters (state estimates) and consequent actions can be evaluated using methods of the statistical decision theory (Chapter 2).
7	This can mean the attachment of different control parameters to the current and desired state and consequent state alternatives and their probabilities.
8	The process can be sequential or parallel, relying on a single decision maker or a group of experts. Subtasks related to SDT process are described in Chapter 2. In case of clustering, prototypes are here interpreted (classified) according to KM process in Section 3.1, and the proposed decision alternative is attached to each of them.

Table 7.6. Use case 3 – Make Decision.

id	Description	Concepts: Stereotype
1	DSS detects a Trigger Condition for a need for decision and shows Decision Proposal to Decision Maker.	DSS: System Trigger Condition: Action Decision Proposal: UserElement Decision Maker: Role
2	Decision Maker selects Decision Alternative to be inspected.	Decision Alternative: DecisionModelElement
3	DSS shows Decision Model information related to the Decision Alternative.	Decision Model: UserElement
4	Decision Maker inspects and alters the Decision Scenario related to Decision Alternative. Decision Maker can propose a Configuration Change Request.	Decision Scenario: UserElement Configuration Change Request: Document
5	DSS generates and shows new Decision Alternative.	
6	Decision Maker makes Decision, documents it, and stores the Session with its Decision Documentation to Decision History Database.	Decision: Action Decision Making Process: Process Decision Session: Data Decision Documentation: Document Decision History Database: Database
7	DSS captures all relevant Consequences of the Decision made, if possible.	Consequence: Document

Table 7.7. Notes for use case 3.

Step	Note
	Steps 2–5 can occur in any order and many times.
2	Alternatives can be, for example, state change history of the cluster model that documents the influence of the different actions (process control adjustments) with respect to states (clusters).
3	This information can be an illustration of posterior probability densities for SDT (Chapter 2) or a visualization of process data and cluster evolution (Section 3.1). For example, taking action A when the process is in cluster (state) 1 leads to the state change from cluster 1 to cluster 3 with 90% probability and to cluster 5 with 5% probability. Decision Maker can also explore the previous decision making sessions, their decisions and the resulting consequences. These are recommended in the order of relevance related to current Decision Alternative.
4	When using clustering, the Decision Maker could change or request a change on the number of cluster prototypes (state estimates), clustering principle (e.g., different distributional assumptions) etc. (Section 3.1).
6	Decision Maker may accept a Decision Alternative, decide not to make a Decision, or cancel the Decision Making Process.

Table 7.8. Use case 4 – Maintain DSS.

Id	Description	Concepts: Stereotype
1	DSS Configuration Team receives Configuration Change Request related to the set of supported Decision Tasks from Change Requester.	DSS Configuration Team: Role Change Requester: Role Configuration Change Request: Document Decision Task: UserElement
2	DSS Configuration Team accepts or rejects the Configuration Change Request based on stored Decisions in Decision History Database and available information on documented Consequences of Decisions made.	Decision History Database: Database Decision: Action Consequence: Document
3	Method Expert modifies the set of available Decision Support Techniques and stores the results to Method Library.	Method Expert: Role Decision Support Technique: DecisionModelElement Method Library: System
4	DSS Configuration Team modifies the set of organizational Decision Tasks.	
5	DSS Configuration Team documents the changes in Decision Tasks, stores the Decision Tasks and Change Documentation to Decision Template Database, and notifies the Change Requester and other relevant users.	Change Documentation: Document Decision Template Database: Database

Table 7.9. Notes for use case 4.

Step	Note
1	DSS Configuration Team should have regular meetings to assess DSS and change requests.
2	If possible, DSS captures the Consequences of the Decisions. Consequences can also be documented manually.
	Steps 3–5 are performed only if Configuration Change Request was accepted in Step 2.
3	New, but presumably more complex computational tools and techniques appear rapidly and regularly.
4	This is an example of learning organization.
5	DSS Version Control database itself creates organizational memory concerning DSS life-cycle. Learning from the past can be supported e.g. by text mining techniques, e.g. (Nurminen et al. 2005).

7.3.2 Entity model

Use cases describe the problem domain in one viewpoint. The information is mostly not properly organised for software development. The development process can be further facilitated by extracting a domain model from the use cases. We encoded the use cases in ProcML – a semistructured XML format that allows attaching metadata to use case steps, such as conceptual stereotypes *role* and *database* (Nurminen et al. 2007). It is also possible to transform the specification to a website, allowing easy searching and browsing of the use cases. Use cases expressed in XML were subsequently analyzed by UCOT (Use Cases to Original entities) software (Kärkkäinen et al. 2008) to automatically generate a conceptual model based on the analysis. A grammatical parser (http://nlp.stanford.edu/software/lex-parser.shtml) and Abbott's heuristic (Abbott 1983) were used to process the use cases. In this section, we describe the entity model and evaluate the modeling process.

Figure 7.4 illustrates an unmodified, automatically generated entity model. As such, the model is not very useful because of the limitations in heuristic and natural language parsing. After initial processing the conceptual model was refined manually using UCOT by merging duplicate entities and dividing entities that represent multiple concepts. Subsequently, attribute and relation information was adjusted to reflect the actual application domain. A few nonessential entities and relations were omitted to make the model easier to understand. Finally, stereotypes were added to some of the concepts. The final model is illustrated in Figure 7. and shows approximately how different entities of the system act together. The model can be used in subsequent development phases of the system.

Although the use cases were mostly written using strict conventions (e.g. using subject-predicate-object structure), it proved to be exceedingly difficult to stick with simple sentence structures. The use cases were iterated many times with four different authors and as the domain understanding increased, the complexity of the sentences increased as well. For example, clauses like "if necessary" were added and multiple related actions of a single actor were combined to a single step. A specific problem (that can still be seen from the final model) was the complex relationship between Decision Support Technique, Decision Model, and Decision Task. They are referred to in many use case steps and often in an ambiguous way (e.g. "Method Expert attaches the Decision Support Technique suitable for the Decision Task to Decision Model") that is difficult to interpret automatically.

A known limitation in UCOT data model is the lack of support for n-ary relations. Since the use cases contained many instances of 3-ary relations (e.g. "Decision Configurator stores Documentation to Decision Template Database"), we had to divide the relation to multiple elementary relations (e.g. "Decision Configurator stores Documentation" and "Documentation is stored to Decision Template Database"). In addition, the variation of singular and plural forms, as well as the use of pronouns ("Decision Maker makes Decision and documents it") yielded unnecessary entities that had to be merged. Overall, the system was not very effective in processing long sentences and produced entities that actually contained either multiple concepts (e.g. "Decision Objectives and Decision Alternatives") or both a concept and a relation (e.g. "DSS based on configuration change requests").

Although it is relatively straightforward to "clean up" the model with UCOT after initial processing, maintenance becomes an issue if the use cases are modified after the entity model is modified manually. Since the relations from the entity model are not explicitly linked back to the use cases, it may be necessary to recreate the entity model from scratch after modifications are made in the original use cases. UCOT records all user actions after the model is loaded, so in principle it could be possible to apply some of the changes to the entity model automatically. Another possibility is to extend the ProcML data model with full entity linkage: as the use cases are processed, UCOT would tag each word with related entities. If the use cases are modified, the entity data would be preserved in XML descriptions. Both approaches should be considered for future development.

Based on the entity model, it seems that the roles "DSS Configuration Team", "Decision Configurator", and "Method Expert", as well as databases "Decision Template Database" and "Decision History Database" are highly connected. Other key entities include "DSS", "Documentation", "Decision Task", "Decision Support Technique", and "Decision Model". As noted earlier, many entities starting with word "Decision" are probably more connected than they actually need to be, so careful analysis of their actual relations is needed in the subsequent development phases. At the current state, the model is not as understandable as we had hoped prior to use case specification. However, some hints about the required architecture can be discovered. For example, the activities of “Method Expert” and “System Expert” related to “Decision Support Technique” and “Organizational Data Sources” are somewhat isolated from the rest of the system, so they are candidate entities to be supported as separate (possibly outsourced) components. On the other hand, because of the high connectivity of “Documentation” to many roles and other entities, it might make sense to construct a common documentation system or format to be shared by different roles and subsystems – to be eventually stored in the Decision Template Database.

We emphasize that the modified model is by no means “final” – it merely provides a base for further development phases and should be updated as requirements or use cases change. Being generated from informal descriptions, the entity model does not necessarily represent the exact entities and relations (cf. ER-diagram used in database development) in the system, but helps to find the most essential entities (e.g. entities that are densely connected) that should be concentrated on. Depending on the development methodology, the model can be utilized in various ways. Perhaps the most common way would be to proceed with object-oriented analysis and design, separating classes and objects from the entity model and extending it with more technical detail. The entity model could also be generalized to a domain (meta)model to represent a set of requirements that are common for a set of applications, thus helping the creation of a software product line or a domain-specific ontology.

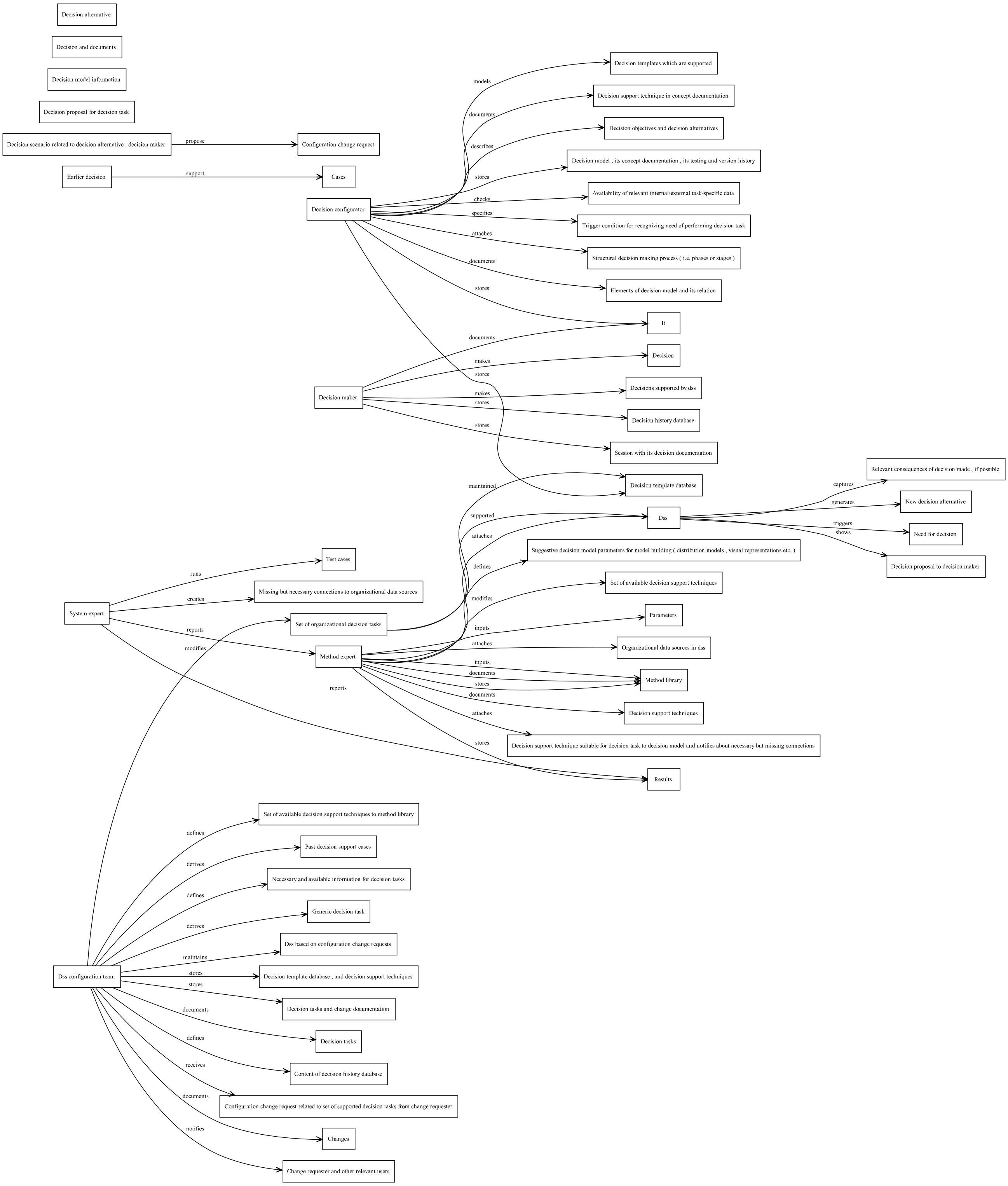


Figure 7.4. DSS entity model based on use cases – initial, automatically generated model.

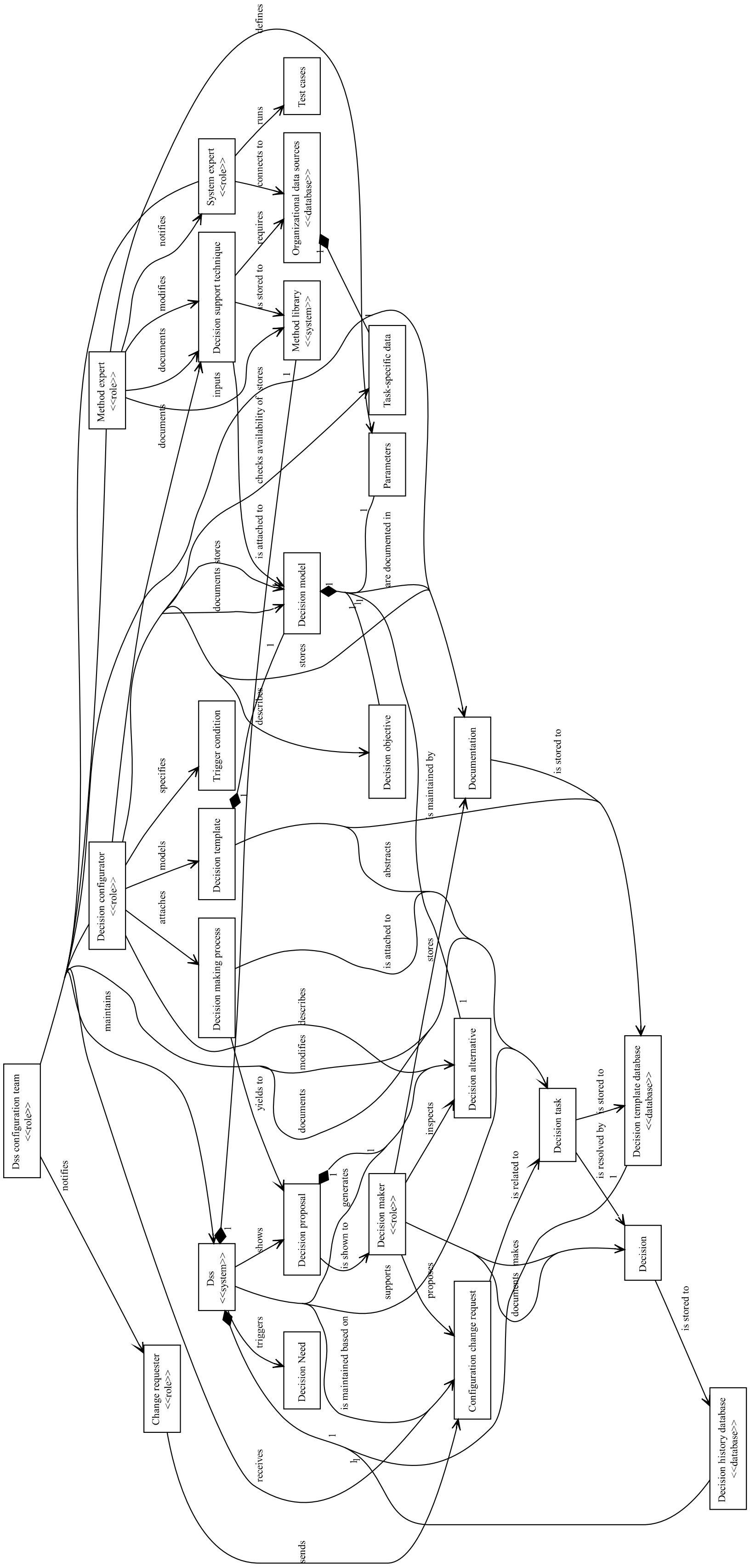


Figure 7.5. DSS entity model based on use cases – manual modifications applied.

7.4 Conclusion

Decision making processes are complex. There are a multitude of approaches and techniques to support decision making in organizations. We have tried to (re)cover all the relevant aspects of ODSS establishing linkage between themes described in the earlier chapters. This joins together the different roles and competences of the consortium project participants.

We have suggested both a new generic use case -based specification for operational decision support systems, as well as a way (stereotyped entity model) to establish a shared ontology between relevant stakeholders. Use cases were originally based on generic user requirements in Appendix A (Jokinen et al. 2008) and generalized in multiple iterations to accommodate different decision support techniques (e.g. statistical decision theory, data clustering). Use cases were expressed in ProcML format, allowing them to be published in a hyperlinked format and further processed by UCOT software. Although somewhat abstract in nature, the use cases clarify especially the organizational context (e.g. roles and information systems) needed to establish a decision support system. The semiautomatically generated entity model points out essential concepts from the problem domain and can be used as a base for more detailed specifications.

As usual on R&D&I, we have obtained results that point to further research. Although the use cases were based on generic user requirements, the explicit link between requirements and use case steps was not preserved. Even though ProcML supports linking requirements to use cases, as the meaning of particular steps were changed or as use cases were split or joined, tracing the original requirements to updated use cases was somewhat cumbersome without further software support. A more serious shortcoming is the lack of linkage between generated entity model and original use cases – the transformation is one-way and in most cases, manual corrections must be made to the entity model every time use cases are changed. In future development, the generated conceptual model should be synchronized with manually specified entities and stereotypes marked in use cases.

Combining use cases to semiautomatically generated, stereotyped entity model seems to be a promising approach for requirements elicitation and conceptual modeling regardless of the methodology (e.g. OOA/D, domain engineering, ontology engineering) used in later development phases. Stereotypes provide essential domain-specific metadata that can be used for code generation and simplify the original use case descriptions. Attaching a stereotype to each concept creates a classification of them, in this way supporting the critical transfer from domain analysis into system development. Some of the stereotypes (e.g. Role, System, Process, Document) are relatively domain-independent, but the exact method to derive different kinds of domain-specific stereotypes (e.g. DecisionModelElement) is yet to be explicated. Ultimately there could be transparent 2-way linking between requirements, use cases, and entities in a unified model residing in a knowledge base. Depending on the modeling task, different views of the model could be exported to achieve significant productivity gains in systems development.

References

Abbott, R. J. (1983) Program design by informal English descriptions. Commun. ACM, Vol. 26, No. 11, pp. 882–894.

Arnott, D. (2006) Cognitive biases and decision support systems development: a design science approach. Information Systems Journal, Vol. 16, No. 1, pp. 55–78.

Bittner, K. & Spence, I. (2002) Use Case Modeling. Addison-Wesley.

Boyd, J. A. (2007) Discourse on Winning and Losing. http://www.d-n-i.net/dni/john-r-boyd/.

Cockburn, A. (1997) Structuring Use Cases with Goals. Journal of Object-Oriented Programming, Sept–Oct and Nov–Dec.

Cockburn, A. (2000) Writing Effective Use Cases. Addison-Wesley.

Davenport, T. H. (1993) Process Innovation – Reengineering Work through Information Technology. Harvard Business School Press.

Gorry, G. & Scott-Morton, M. (1971) A framework for management information systems. Sloan Management Review, Vol. 13, No. 1, pp. 55–71.

Jackson, M. (2001) Problem frames: analyzing and structuring software development problems. Addison-Wesley.

Jokinen, H., Grén, J., Hukki, K., Konkarikoski, K., Kärkkäinen, T., Pulkkinen, U., Ritala, R., Suominen, P. & Ylén, J. (2008) Generic User Requirements for Operational Decision Support System. *To be submitted*.

Kilpeläinen, T. (2007) Genre and ontology based business information architecture framework (GOBIAF). PhD thesis. Jyväskylä: University of Jyväskylä.

Kärkkäinen, T., Nurminen, M., Suominen, P., Pieniluoma, T. & Liukko, I. (2008) UCOT: Semiautomatic Generation of Conceptual Models from Use Case Descriptions. In: C. Pahl (Ed.) IASTED International Conference on Software Engineering (SE 2008). Calgary: ACTA Press. Pp. 171–177.

Lauesen, S. (2002) Software Requirements: Styles and Techniques. Addison-Wesley.

Mann, A. (2002) Risky Business. Columns (UGA Faculty Newsletter).

Nurminen, M., Honkaranta, A. & Kärkkäinen, T. (2005) ExtMiner: Combining Multiple Ranking and Clustering Algorithms for Structured Document Retrieval. In: Proceedings of International workshop on Integrating Data Mining, Databases and Information Retrieval (IDDI'05), 16th International Workshop on Database and Expert Systems Applications. IEEE. Pp. 1036–1040.

Nurminen, M., Honkaranta, A. & Kärkkäinen, T. (2007) ProcMiner: Advancing Process Analysis and Management. In: Proceedings of Workshop on Text Data Mining and Management (TDMM), IEEE 23rd Int. Conf. on Data Engineering. IEEE. Pp. 760–769.

Sharp, A. & McDermott, P. (2001) Workflow Modeling. Artech House.

Simon, H. A. (1965) The New Science of Management Decisions. In: Herbert A. Simon (Ed.) The Shape of Automation for Men and Management. New York: Harper and Row.

Simon, H. A. (1976) Administrative Behavior. 3rd edition. New York: The Free Press.

Soffer, P. & Hadar, I. (2003) Reusability of conceptual models: The problem of model variations. In: K. Siau, T. Halpin & J. Krogstie (Eds.) Proceedings of Eighth CAiSE/IFIP8.1 International Workshop on Evaluation of Modeling Methods in Systems Analysis and Design (EMMSAD'03). Pp. 126–134.

Turban, E., Aronson, J. E. & Liang, T. (2004) Decision Support Systems and Intelligent Systems. 7th edition. Prentice-Hall, Inc.

Wirfs-Brock, R. (1993) Designing Scenarios: Making the Case for a Use Case Framework. The Smalltalk Report, Vol. 3, No. 3.

Zachman, J. A. (1987) A framework for information systems architecture. IBM Syst. J., Vol. 26, No. 3, pp. 276–292.

Summary

The state of art of research scope was studied and the trends which influence the domain were examined. Then the critical approach to operational decision making in the Finnish pulp and paper industry were formed by considering the research target from several view points.

Chapter 2 linked operations activities to business strategy in order to construct a goal basis for operational decision making and its dynamics. In this context the representation of operational decision making as a set of well-defined mathematical models was proposed. Furthermore, Chapter 2 discussed, from a formal point of view, the phases of making operational decisions. In the chapter, it was claimed that the elements of operational decision making are generic and thus provide a basis both for collaborative understanding, and for information system design and implementation. Chapter 2 briefly discussed the apparent contradiction between the requirement of rationality in formal decision theory and subjective behaviour of a human decision maker.

Chapter 3 concentrated on the decision making tasks in process monitoring and diagnostics. Necessity for new techniques for data analysis is clear because of the complexity of the current production systems and the amount of collected data. The scope of the traditional data analysis system is also too narrow. General functionalities were represented in Section 3.2 and applications of clustering methods, genetic algorithms, PCA and causal digraphs were introduced in the following sections. These sections paid attention to reliability and uncertainty, which are relevant components in decision making. Finally, the measures for the maintenance performance were studied. These measures help in organizing or providing of maintenance activities.

In Chapter 4, it was found that people are fallible and they make biased decisions. The human dimension was emphasised in complex situations and while providing support for activities in industrial process operation. The role of decision support systems is undisputable but in designing DSS it is essential to have a clear idea about how people should use them and how the new usage culture can be implemented. It was also noticed that training plans enable cost-effective start-up of new information systems.

Chapter 5 presented a psychological point of view on operational decision making, focusing on the collaboration of people representing different roles in paper production. The approach provides means for analysing the human interactions and for identifying factors that promote effective collaboration in the actor network. Knowledge of these factors can be utilised in the development of collaboration practices and IT support.

Requirements for an IT infrastructure to support decision making and its applications were presented in Chapter 6. These were found by observing decision-making, collaborative decision-making and IT architecture viewpoints. The discussion included the functionality of current IT systems at strategic, tactical and operative levels and also gave product examples. Trends are noticed by introducing the newest standards and technologies which enable more flexible systems and decision making support at logic level. At the end, a proposal for a new IT architecture is presented and a place of new standards and technologies are shown in this context.

The final chapter concluded aspects of organisational and technical views. Guidelines to apply these views for decision making systems specification were given. As an example, the use case paradigm was introduced and utilised for domain specific and generic user requirements. A business-use-case-type specification of a hypothetical operational decision support system was presented. The DSS domain was further described by a semi-automatically generated conceptual model based on the use cases. These can be used to set fixed and common terms among the decision making participants and utilised in decision support system design.

The multidisciplinary approach presented covered operative decision making from several viewpoints, considering nuances and context in which real decisions are made today and in the future. The publication is an illustrative example of a holistic conception which can be achieved by utilising multidisciplinary know-how in a restricted scope.

Appendix A: Generic user requirements for decision support systems

Generic user requirements for pre-structured decision tasks

GURs for generating and justifying decision proposals.

GUR label	GUR title	Description
GUR-1.1.1	Notify the user about a need to make a decision and act	Based on the measurements and models available, the DSS notices a situation that needs a decision to be made and brings this need to the user's attention.
GUR-1.1.2	Generate a proposal for a decision	Using data and models available, and by solving an optimization task a proposal is generated and presented to the user without any additional information.
GUR-1.1.3	Present the concep-tualization of system state, consequences and description of decision alternatives	Based on the measurements, system state descriptions and event history, the current system state is described with given concept system and all potential decision alternatives are presented in an understandable and acceptable form, and on request the consequences of user selected decision alternatives are presented.
GUR-1.1.4	Present measurement information relevant for decision to be made	The measurement data utilized in generating the decision proposal or elected by the user is presented; using available and suitable methods the uncertainty and reliability of the data is assessed and presented in an understandable and acceptable form.
GUR-1.1.5	Present the relevant state estimation and prediction models, their estimation and prediction results and uncertainties in them	Concerning the current decision proposal or user specified decision candidate, the relevant state estimation and prediction models are selected and visualized, and the produced estimation and prediction results with uncertainties are presented in an understandable and acceptable form.
GUR-1.1.6	Present the relevant objective(s) and the decision time horizon	The objectives used in the generation of decision proposal or user specified decision candidate, possibly by using a number of optimization time horizons, are presented to the user in an understandable and acceptable form.
GUR-1.1.7a	Present the degree of satisfaction of different objectives in multi-goal decision making	Given a decision proposal or user specified decision candidate the values of objectives and the level of satisfaction is presented to the user in an understandable and acceptable form. Also the measurement principle of the objective satisfaction is presented for the users. The motivation of the measurement principle is derived form the higher level objectives of the company.
GUR-1.1.7b	Present trade-off possibilities in multi-goal optimization	The trade-off ratios between the decision objectives are presented for the users in an understandable and acceptable form. One or several of the objectives may describe the attitude towards risk. The favored trade-off is motivated.
GUR-1.1.8	Show the robustness of proposed decision to user selected model *parameters*	Concerning the system state and prediction models used in generating the decision proposal, the sensitivity of this proposal is analyzed with respect to variations in parameters selected by the user. The sensitivity is visualized and presented in an understandable and acceptable form.
GUR-1.1.9	Analyze the robustness of proposed decision towards variations in user selected model *structures*	Concerning the system state and prediction models available in generating the decision proposal, the robustness of this proposal is analyzed towards variations in model structures selected by the user. The results of the robustness analysis are presented in an understandable and acceptable form.

GURs for modifying and developing a proposed decision.

GUR label	GUR title	Description
GUR-1.2.1	What-if analysis	The DSS allows the user to select alternative sets of measurement data and/or to change the parameters of state estimation models, prediction models and/or objectives to generate alternative decisions.
GUR-1.2.2	Manage the alternative decisions and their background material in a tree graph	The user is provided with an interface to manage alternative decisions and their background materials in a tree structure where a node is a fully structured decision task and a generated proposal and a link from one node to another specifies the change in decision task structure.
GUR-1.2.3	Facilitate group discussion about generating a consensus decision	The need and subjects for group discussion are noticed for users. The differences in initial structures are analyzed and a tree-like graph is generated from the initial structures. Through a process, a protocol and a template the group jointly modifies and develops the graph of decision structures further so that a consensus structures is specified. The graph documents the development of the consensus structure and the relationship between the initial structure and the consensus structure.
GUR-1.2.4	Facilitate group discussion about generating a decision by managing a hierarchy of alternative decisions and their background material, in particular conflicting objectives	The need and subjects for group discussion are noticed for users. The differences in initial structures are analyzed and a tree-like graph is generated from the initial structures. Through a process, a protocol and a template the group jointly modifies and develops the graph of decision structures without the objectives. Once a consensus structure has been achieved, a new decision task with the consensus structure complemented with all the initial objectives is formed. The decision proposal of this structure, the corresponding trade-off and level of satisfaction are analyzed in a joint session.

GURs for utilizing and storing experiences.

GUR label	GUR title	Description
GUR-1.3.1	Store a decision making session, link to future assessment	While the decision making session is carried out, the system stores all actions by the user so that the session can be rerun at any later time. As the user will make reference to process data in relative time, the session stores both the absolute time and relative time references to data so that the session can be rerun with original data or with the data of the rerun instant (see GUR-1.3.2). The user may specify future (over a user specified time interval) measurement data to be linked with the session. Such data would allow assessing the decisions that eventually were made and the system performance as a result of the decisions.
GUR-1.3.2	Retrieve similar decision making situations with link to follow-up (what really happened)	The DSS organizes the stored sessions for the end user in the order of similarity (measures of similarity: level 1 decision task; level 2 time since session; level 3 input data current vs. the one at the time of creation of session) and allows the user to rerun the session in one go or in steps with either the original data or present data.

Generic user requirements for structuring and analyzing decision tasks

GURs for structuring decision tasks.

GUR label	GUR title	Description
GUR-2.1.1	Specify condition for recognizing the need of making the decision	1) The user specifies a condition where some input from outside of the system is needed, i.e. decision making is needed. 2) An automated system can also be constructed to observe such situations when decision making is needed.
GUR-2.1.2a	Specification of system state space description	The user describes the specification of system state space with the possible aid from DSS. The specification concerns current decision task being structured.
GUR-2.1.2b	Specification of measurements available	The user lists the measurements available for the system and links the measurement names in data source to the names to be used in the DSS.
GUR-2.1.2c	Specification of information available	The user lists the information (*a priori*) available for the system.
GUR-2.1.3	Specification of decision consequence space description	The user describes the specification of decision consequence space with the possible aid from DSS. Specification includes the time horizon in dynamic optimization. The specification concerns current decision task being structured.
GUR-2.1.4	Specification of decision space	The user describes the specification of decision space with the possible aid from DSS. Specification includes the decision interval in dynamic optimization. The specification concerns current decision task being structured.
GUR-2.1.5	One-by-one specific-ation of objectives as deterministic functions from consequence space to real numbers	The principle for defining measurement principle of the objective satisfaction for each objective is presented for the users (in a form of a template) The procedure for taking the higher level objectives of the company is described. The possibilities of different measuring principles are presented. The objective is specified as mappings from the consequence and decision space to real numbers
GUR-2.1.6	Specification of multiple and depend-ent objectives as deterministic functions from consequence space to real numbers	The principles for determining (additive) multi-objective value functions or multi-objective value models are presented. The objectives are specified as mappings from the consequence and decision space to real numbers.
GUR-2.1.7	Specification of attitude towards risk	The user specifies the attitude towards risk with assisted by the DSS. Descriptions may be based on utility, risk premium, or constraining the probabilities of unfavorable values of objectives.
GUR-2.1.8	Specification of inequality constraints in the decision space	The user describes the constraints in the decision space with assisted by DSS.
GUR-2.1.9	Specification of inequality constraints in consequence space	The user describes the constraints in the consequence space assisted by DSS. A constraint in consequence space can also be defined by constraining a specified objective.
GUR-2.1.10	Specification of other forms of constraints	Not all possible constraints are constraints entirely describable as those in decision space or consequence space. This requirement covers such additional constraints.

GUR-2.1.11	Specification of measurement information derivable from measurement data	The user specifies the forms of measurement information derivable from measurement data.
GUR-2.1.12a	Specification of state estimation model	The user has an access to a system database containing a set of state estimation models. The user selects a model and specifies the inputs to the model as measurement data or measurement information. The user may modify the structure of the model used.
GUR-2.1.12b	Specification of state recognition method	The user has an access to a system database containing a set of state recognition methods. The user selects a model and specifies the inputs to the model as measurement data or measurement information. The user may modify the structure of the model used.
GUR-2.1.13	Specification of consequence prediction model	The user has an access to a system database containing a set of consequence prediction models. The user selects a model and specifies the inputs as measurement data, measurement information or outputs of system state estimation model, and as decisions. The user may modify the structure of the model used.
GUR-2.1.14	Specification of optimization method to be used in the generation of decision proposal	The system has a library/database of optimization methods with documentation about in which case each of the methods is suitable, which are its parameters and instructions on how to choose them. The specification concerns current decision task being structured. This GUR requires that the user is educated concerning optimization methods.
GUR-2.1.15	A guided tour for structuring a decision task	The guided tour organizes the tasks corresponding to GUR-2.1.1-14 into a session that guarantees all the necessary definitions to be made for the decision task to be formally correctly structured. NOTE: as all well-structured decision support systems need not address all GUR-2.1.1-14 requirements, the guided tour has several exit points. The definition of well-structured problem is closely related to use cases supported.
GUR-2.1.16	Facilitate group work during the specification process	An approach for identifying the need of group work is provided. Support for identifying sufficient set of participants, and their roles for the group work is given. The system supports the specification tasks of GUR2.1.1-14 or the guided tour of GUR2.1.15 to be carried out in a joint discussion sharing the tool and the structures over the network.
GUR-2.1.17		
GUR-2.1.18	Maintain long term history of decision support structures	Version management of decision structures with documentation.
GUR-2.1.19	Allow to document the choice of structures	Generates a structured document documenting the decision support structure. Can be filled during the specification process or once the structure is fully defined. Mainly for documenting systems set up for permanent use, but can be used also in documenting ad hoc decision making.
GUR-2.1.20	Manage the portfolio of structured decision tasks	A user interface for the database of supported structured decision tasks. At first level lists the supported tasks. At second levels describes the task structures. At third level allows access to all recorded decision sessions. The user may select existing structured decision tasks as a basis for generating a new structured decision task. The user interface supports virtual group work on the tasks.

GURs for tuning parameters for decision tasks.

GUR label	GUR title	Description
GUR-2.2.1	Present all the decision support parameters to be set	The user is provided with a list of all relevant parameters needed to be set in tuning the support for a decision making task.
GUR-2.2.2	Provide an interface to set all the decision support parameters	The user is given an access to modify the decision support parameters.
GUR-2.2.3		
GUR-2.2.4	Support identifying parameters in state estimation, consequence prediction and objective functions with history data	In order to find a set of parameters for the decision task, the user may use history data to identify the state estimation and prediction model parameters.
GUR-2.2.5	Support testing the DSS with user specified data	The user may shift the present time to some earlier instant about which history data is available. For data not available through history data base, the user may specify fictitious data, e.g. through excel sheets or as program expressions.
GUR-2.2.6	Manage the alternative sets of decision support parameters and their test results	The user is provided with a user interface for the database to store and retrieve any alternative sets of decision support parameters and their test results.
GUR-2.2.7	Support tuning and testing of parameters as group work	Provides a format for making expert judgments for the values of parameters. Judgments can be combined and uncertainties assessed. The system supports the tuning tasks of GUR-2.2.1-6 to be carried out in a joint discussion sharing the tool and the structures over the network. Each group member may work individually to identify a subset of parameters. DSS will combine such individual pieces of work to a single set of parameter values or their alternative values to be further discussed within the group.
GUR-2.2.8	Maintain long term history of tunings and their tests	Shows the history of structure describing the decision task. Allows reverting to some any earlier version.
GUR-2.2.9	Allow to document the choice of parameters	Allows inputting text to explain why a particular value of parameter has been chosen.

Series title, number and report code of publication

VTT Research Notes 2442
VTT-TIED-2442

Author(s)
Mätäsniemi, Teemu (Ed.)

Title

Operational decision making in the process industry
Multidisciplinary approach

Abstract

The publication introduces a multidisciplinary approach to operational decision making (operation and maintenance) applied in the Finnish pulp and paper industry. The purpose of the approach is to produce knowledge and methods that support each other and which can be used to improve the support for operational decision making in the declared scope.

At the beginning, the current challenges and trends are studied. Then, the selected approaches (normative view, process monitoring and diagnostics view, human dimension, collaborative view, standards and IT technologies) are represented. Finally, these themes are joined together by introducing an example.

ISBN
978-951-38-7222-9 (soft back ed.)
978-951-38-7223-6 (URL: http://www.vtt.fi/publications/index.jsp)

Series title and ISSN	Project number
VTT Tiedotteita – Research Notes 1235-0605 (soft back ed.) 1455-0865 (URL: http://www.vtt.fi/publications/index.jsp)	732-G5SU00956

Date	Language	Pages
August 2008	English, Finnish abstr.	133 p. + app. 5 p.

Name of project	Commissioned by
Production2010/ProductionPro	Tekes, Metso Corporation, Myllykoski Corporation, IBM Corporation, Stora Enso, Jyväskylän Teknologiakeskus Oy, Group Intelligentia Oy

Keywords	Publisher
decision making, operation, maintenance, process industry, information management, measurement, optimization, uncertainty, fault isolation, fault diagnosis, collaboration	VTT Technical Research Centre of Finland P.O. Box 1000, FI-02044 VTT, Finland Phone internat. +358 20 722 4404 Fax +358 20 722 4374

Julkaisun sarja, numero ja raporttikoodi

VTT Tiedotteita 2442
VTT-TIED-2442

Tekijä(t)
Mätäsniemi, Teemu (toim.)

Nimeke

Operatiivinen päätöksenteko prosessiteollisuudessa
Monitieteellinen lähestymistapa

Tiivistelmä

Tämä julkaisu esittelee monitieteellisen lähestymistavan operatiiviseen (operointi ja käynnissäpito) päätöksentekoon. Sovelluskohteena on suomalainen paperi- ja selluteollisuus. Lähestymistavan tarkoituksena on tuottaa uutta tietämystä ja menetelmiä, joilla voidaan tukea operatiivista päätöksentekoa ja parantaa päätöksenteon tukijärjestelmiä.

Aluksi esitellään teollisuudenalan nykytilanne ja muutostrendit, minkä jälkeen käydään läpi valitut lähestymistavat (normatiivinen, monitorointi ja diagnostiikka, ihmis- ja yhteistyönäkökulma ja standardi sekä IT-teknologiakatsaus) ja niiden tuottamat tulokset. Lopuksi kokonaisuutta esitellään esimerkin avulla.

ISBN
978-951-38-7222-9 (nid.)
978-951-38-7223-6 (URL: http://www.vtt.fi/publications/index.jsp)

Avainnimeke ja ISSN	Projektinumero
VTT Tiedotteita – Research Notes 1235-0605 (nid.) 1455-0865 (URL: http://www.vtt.fi/publications/index.jsp)	732-G5SU00956

Julkaisuaika	Kieli	Sivuja
Elokuu 2008	Suomi, engl. tiiv.	133 s. + liitt. 5 s.

Projektin nimi	Toimeksiantaja(t)
Production2010/ProductionPro	Tekes, Metso Corporation, Myllykoski Corporation, IBM Corporation, Stora Enso, Jyväskylän Teknologiakeskus Oy, Group Intelligentia Oy

Avainsanat	Julkaisija
decision making, operation, maintenance, process industry, information management, measurement, optimization, uncertainty, fault isolation, fault diagnosis, collaboration	VTT PL 1000, 02044 VTT Puh. 020 722 4520 Faksi 020 722 4374

The publication introduces a multidisciplinary approach to operational decision making (operation and maintenance) applied in the Finnish pulp and paper industry. The purpose of the approach is to produce knowledge and methods that support each other and which can be used to improve the support for operational decision making in the declared scope.

At the beginning, the current challenges and trends are studied. Then, the selected approaches (normative view, process monitoring and diagnostics view, human dimension, collaborative view, standards and IT technologies) are represented. Finally, these themes are joined together by introducing an example.

Julkaisu on saatavana	Publikationen distribueras av	This publication is available from
VTT PL 1000 02044 VTT Puh. 020 722 4520 http://www.vtt.fi	VTT PB 1000 02044 VTT Tel. 020 722 4520 http://www.vtt.fi	VTT P.O. Box 1000 FI-02044 VTT, Finland Phone internat. + 358 20 722 4520 http://www.vtt.fi

ISBN 978-951-38-7222-9 (soft back ed.)
ISSN 1235-0605 (soft back ed.)

ISBN 978-951-38-7223-6 (URL: http://www.vtt.fi/publications/index.jsp)
ISSN 1455-0865 (URL: http://www.vtt.fi/publications/index.jsp)