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# PLANT PERFORMANCE EVALUATION IN COMPLEX INDUSTRIAL APPLICATIONS

Vesa Hölttä

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Vesa Hölttä

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Abstract

In large-scale industrial plants, investment and maintenance decisions should be based on quantitative knowledge about the factors that reduce overall performance. This is impossible without sound and objective methods for producing the necessary performance information. The need for performance assessment spans from low-level control loops to the business process level. Since the number of control loops in an industrial plant can be in the order of hundreds or thousands, it is infeasible to monitor their performance manually.

This thesis proposes a set of performance indices for two-dimensional web processes, found, for example, in the paper, metal, and plastic industries. A scaling function approach where different performance indices are scaled to the interval $0 \ldots 100$ is introduced in order to enable the creation of a hierarchical performance assessment framework. A simulation example and two large-scale industrial applications illustrate the creation and usage of this performance evaluation framework.

When the values of all performance indices are in the same range and are interpreted in the same way, evaluating performance becomes less demanding and time-consuming. This thesis demonstrates that a number of low-level performance indices can be aggregated into a small amount of high-level indices which still contain the relevant information. To assess process performance, it suffices to monitor the high-level indices, and only if an anomaly is detected, there is need to investigate low-level performance information.

This thesis shows that by processing and combining low-level performance data coming from different sources, it is possible to obtain performance information that is easier to interpret for humans. This information can then be utilized in decision making. The performance assessment systems created for the industrial applications are in production use at the moment of publishing the thesis.

Keywords Control loop performance assessment, performance index, process monitoring, industrial implementation

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Tiivistelmä

Teollisen mittakaavan tuotantolaitoksissa investointi- ja huoltopäätösten tulisi perustua määrälliseen tietämykseen kokonaissuorituskykyä heikentävistä tekijöistä. Tämä on mahdotonta ilman luotettavia ja tasapuolisia menetelmiä, joilla pystytään tuottamaan tarvittava suorituskykytieto. Suorituskyvyn määrittämisen tarve ulottuu alatason säätöpiireistä liiketoimintaprosesseihin. Koska teollisuuslaitoksessa voi olla satoja tai tuhansia säätöpiirejä, niiden valvonta henkilötyönä ei ole toteuttamiskelpoinen ratkaisu.

Tässä väitöskirjassa esitetään joukko suorituskykyindeksejä kaksiulotteisille rainaprosesseille, joita on esimerkiksi paperi-, metalli- ja muoviteollisuudessa. Kuvaamalla erilaiset suorituskykyindeksit välille $0 \ldots 100$ mahdollistetaan hierarkkisen järjestelmän luominen suorituskyvyn seuraamista varten. Simuloitu esimerkki ja kaksi suuren kokoluokan teollista sovellusta havainnollistavat seurantajärjestelmän luomista ja käyttöä.

Kun kaikkien suorituskykyindeksien arvot ovat samalla välillä ja niitä tulkitaan samoin, suorituskyvyn määrittämisestä tulee aikaisempaa helpompaa ja vähemmän aikaa vievää. Tässä väitöskirjassa näytetään, että joukko alatason suorituskykyindeksejä voidaan yhdistää muutamaksi korkean tason suorituskykyindeksiksi, jotka sisältävät edelleen olennaisen tiedon. Prosessin suorituskyvyn arviointia varten riittää seurata korkean tason indeksejä, ja ainoastaan jos poikkeamia ilmenee, alatason tunnuslukuja tarvitsee tutkia.

Tämä väitöskirja osoittaa, että eri lähteistä saatavaa alatason suorituskykytietoa jalostamalla ja yhdistämällä informaatio on mahdollista saada ihmisille helpommin ymmärrettävään muotoon. Tätä tietoa voi hyödyntää päätöksenteon apuna. Teollisia sovelluksia varten kehitetyt suorituskyvyn arvioinnin järjestelmät ovat tuotantokäytössä väitöskirjan julkaisuhetkellä.

Asiasanat Säädön suorituskyvyn arviointi, suorituskykyindeksi, prosessien monitorointi, teollinen soveltaminen

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# Preface

The research for this thesis was carried out at the Control Engineering Group of the Helsinki University of Technology. The head of the group, professor Heikki Koivo employed me, a second year undergraduate student, in the year 2000. Heikki, I thank you sincerely for the interesting research topics and mentorship you have provided me with ever since, as well as for the relaxed and innovative atmosphere in the group.

Many thanks are due to Jari Hämäläinen (VTT Technical Research Centre of Finland) and Matti Vilkko (Tampere University of Technology), for thoroughly pre-examining this thesis and for providing valuable comments and criticism that helped me to improve the quality of my work, and to William Martin for proof-reading the manuscript. I thank professor Sylviane Gentil (Grenoble Institute of Technology) for the possibility to visit her group, and for our discussions that made me think some things over.

The aim of this thesis was to study performance assessment and to apply it to relevant real-world problems. This would not have been possible without our industrial partners. During the years that I have worked together with Arto Peltomaa of John Deere Forestry, he has demonstrated numerous times his unprejudiced attitude towards our ideas, and made us believe in them. I also thank Aki Putkonen for sharing his knowledge on forest machines. Pasi Koskela of Sappi Kirkniemi Mill gave the initial push to my contribution to the paper industry. His enthusiasm was an essential driving force in this part of my research. Jarkko Savinainen was the man who made things work at the mill.

I offer my sincere thanks to all those who have worked with me during my thesis project. The industrial implementations described in this thesis have required dozens and dozens of man-months of programming, something that I would not have been able to do on my own.

My research was partly funded by the Graduate School in Electronics, Telecommunications and Automation. I am grateful also to the Walter Ahlström foundation, the Finnish Foundation for Economic and Technology Sciences – KAUTE, the Neles Corporation 30-year Anniversary Foundation, and the Finnish Society for Automation for additional financial support. The project funding provided by the Finnish Funding Agency for Technology and Innovation (Tekes), as well as by the companies involved in the projects is gratefully acknowledged.

The Control Engineering Group consists of a bunch of great, talented and mad scientists. It is a privilege to work with the top researchers on the top floor. Timo and Lasse, thank you for the coffee breaks – something invariant amidst all the waves of change.

Friends and family have been an invaluable resource in my life, providing company, meatballs as well as other foodstuffs, babysitting, etc. I am grateful to my parents and my brother for the numerous ways they have supported me, and especially to my mother who taught me the basics of scientific research.

Valtteri, you have been an excellent assistant in many home improvement projects, and have the ability to growl a joke to make adults laugh (at themselves). I thank you also for your contribution to Figure 2.3. Vendla, it is good to leave for work when you wave me goodbye, but even better to come home and to hear “Moi!” and the sound of your small feet as you come to hug dad. I hope that you both find happiness in your lives, and that I find ways to support you.

Veera, I love you. Thank you for regarding my thesis as important and for being there for me.

Vesa Hölttä

# List of abbreviations

| | |
|---|---|
| CAN | controller area network |
| CD | cross direction |
| COM | component object model |
| CORBA | common object request broker architecture |
| CPA | control performance assessment |
| DCOM | distributed component object model (COM) |
| DCS | distributed control system |
| ERP | enterprise resource planning |
| FDI | fault detection and identification |
| IAE | integral of absolute error |
| ISE | integral of squared error |
| ITAE | integral of time-weighted absolute error |
| ITSE | integral of time-weighted squared error |
| MD | machine direction |
| MES | manufacturing execution systems |
| ODBC | open database connectivity |
| OLE | object linking and embedding |
| OPC | object linking and embedding (OLE) for process control |
| PE | permanent error index |
| PI | proportional-integrating |
| PID | proportional-integrating-derivative |

| | |
|---|---|
| RMI | remote method invocation |
| SCADA | supervisory control and data acquisition |
| SL | sluggish control index |
| SQL | structured query language |
| VBA | Visual Basic for applications |
| XML | extensible markup language |

# List of symbols

| | |
|---|---|
| $\eta$ | arbitrary performance measure |
| $\gamma$ | forgetting factor |
| $\mu$ | arithmetic mean |
| $\sigma$ | standard deviation |
| $d$ | delay |
| $e$ | control error |
| $G$ | transfer function |
| $H$ | arbitrary performance metric |
| $I$ | arbitrary performance index |
| $k$ | time instant (discrete time) |
| $s$ | Laplace variable |
| $t$ | time instant (continuous time) |
| $u$ | input signal |
| $w$ | weighting coefficient |
| $y$ | output signal |
| $y_r$ | reference signal |
| $z^{-1}$ | unit backward shift operator |

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# 1 Introduction

## 1.1 Background and motivation

Large-scale industrial production plants found, for instance, in the steel, chemical, and paper industries, are complex processes from the engineering point of view. Except for small-scale subprocesses, they are mostly beyond exact mathematical modelling because of nonlinear, time-variant, and unknown process dynamics, interactions, and disturbances. In addition to the physical devices that comprise the plant, there are production, maintenance, customer service, and management teams, all having their requirements and opinions regarding optimal operation of the plant. This adds to the overall complexity of the system.

Knowledge of plant performance aids the owner in deciding whether the facility performs well, and if this is not the case, where to look for the problem. Obtaining an overall view of plant performance and finding the weak links is a demanding task. A decrease in performance may have a variety of reasons, for example, incorrect controller tuning, incipient faults in the system, or poor operating practices. The objective of performance monitoring is to enable tracing and fixing problems before they cause poor-quality products to be manufactured and excessive financial losses.

The human side of performance assessment must also be taken into account. The different personnel groups can have mutually contradictory objectives, for example, the salaries of the production team might depend on the amount of production, leading to the desire to maximize output. This will most likely have unfavorable side effects, such as the deterioration of product quality, resulting in an increased workload for the customer service in the form of more complaints. Hence, customer service would prefer a slower production rate with an emphasis on quality. The high dimensionality of the data space in industrial processes implies that a human operator will have difficulties when monitoring the process: it is difficult to take into account the interactions between process variables, for example, when trying to determine the reason for unsatisfactory performance.

The above leads to a need for well-defined performance measures that describe plant performance in an objective and balanced manner. Due to the complexity and large amount of data, performance assessment should be systematic, and automatized such that it is possible to provide the decision makers on different operational levels of the plant with relevant and concise information to be used in the decision making process.

Performance assessment is very closely connected to the field of fault detection and identification (FDI). This is because faults often develop gradually: an incipient fault will not stop the plant, but will result in poorly performing control loops. These control loops can be detected by means of performance assessment, and the fault resulting in degraded performance can be remedied before it causes an unexpected shutdown.

Fault detection and condition monitoring methods are usually divided into three main categories: model-based, knowledge-based and data-driven systems (Chiang *et al.*, 2001). In model-based methods a mathematical model (usually a differential equation system) is built for the monitored system from physical principles and the predictions given by this model are compared with the actual measurements from the system to detect faults (Patton *et al.*, 2000). The main limitation with this approach is that many systems are too complex to allow any sufficiently accurate model to be built, and the models need to be updated to reflect changes in the plant. Often fault situations are handled by ad-hoc procedures developed by human experts. Knowledge-based methods (e.g. expert systems, fuzzy logic) try to automate the use of this knowledge. The problem with these methods is that it has proven out to be very tedious to gather knowledge from the experts and to maintain the knowledge database as products evolve. For a review of FDI methods, see the series of articles by Venkatasubramanian *et al.* (2003*b*; 2003*a*; 2003*c*) or the textbook by Chiang *et al.* (2001).

Most of the research effort in the field of FDI has concentrated on model-based fault diagnosis of a specific device. Examples of this type of research can be found, for example, in (Patton *et al.*, 2000). Model-based methods are particularly fit for applications which are replicated millions of times, such as hard disk drives. The contrast is clear with respect to industrial applications where every control loop of a plant may be different (Thornhill and Shah, 2005).

The approach used in this thesis is data-driven. Data-driven methods try to deduce the properties of the system more or less directly from the available measurement data, which are usually readily available in modern production plants and working machines.

## 1.2 Objectives

In order to thoroughly assess the performance of an industrial process, the following steps need to be taken (Harris *et al.*, 1999; Jelali, 2006):

1. Determination of the capability of the control system
2. Development of suitable statistics for assessing system performance
3. Determination of the reference values for the selected statistics
4. Assessment and detection of control loops having poor performance
5. Development of methods for diagnosing the causes of poor performance
6. Suggestion of improvement measures

The objective of this thesis is to propose a unified performance evaluation framework that addresses items from 1 to 4 from the list above. The framework enables the creation of different points of view to performance on plant level, as well as detailed analysis of low-level performance indicators in the case that high-level indicators show suboptimal behavior. With the framework, it is possible to obtain an overview of the performance of the plant at a glance without a complex analysis and comparison of different performance measures. Two large-scale industrial examples are provided to demonstrate the feasibility of the framework.

The following requirements were set to the plant performance assessment framework:

1. Assessment must be possible without additional measurements. New (physical) measurement points have initial and maintenance costs. In modern production plants, the number of measurements is already high, and extracting useful information from these measurements adds to their value.
2. Setting up the assessment framework should not be laborious, and it should be as automatic as possible.
3. The performance indices must be easy to understand. In order to be able to explain the meaning of the performance indices to plant personnel with different educational backgrounds, the indices must be intuitive and they should measure a concrete target.
4. The performance assessment system should give high-level information at a glance and be able to direct the users' attention to areas with improvement potential. It cannot be expected that users have unlimited time to go through different performance indicators.
5. The performance assessment system should give information that is detailed enough to find the sources of degraded performance.

## 1.3 Contributions

The author's contributions can be summarized as follows.

- Development of performance indices for two-dimensional web processes.
- Development of best practices for data acquisition and storage for performance evaluation.
- Development of a performance evaluation framework that can aggregate arbitrary performance indices.
- Implementation of a performance evaluation framework in two large-scale industrial processes.

## 1.4 Structure

This thesis is organized as follows. Methods and metrics that can be used in controller performance assessment are reviewed in Chapter 2. Before performance assessment is possible, effort is needed to access the measurement data and other information that is needed for the computation of a certain metric. The data must be preprocessed before any analysis to have them in the correct format, to remove outliers, as well as to find different operating points and similar special characteristics of the data. These issues are addressed in Chapter 3. Novel metrics for performance assessment of two-dimensional web processes are proposed in Chapter 4. Chapter 5 describes how a plant-wide performance assessment system is created from the low-level performance indices discussed in the previous chapters. Chapter 6 presents a simulation example, while Chapter 7 and Chapter 8 provide two industrial applications.

# 2

# Review of controller performance evaluation

This chapter presents the history of process performance evaluation. Traditional and state-of-the-art performance indices are reviewed.

Modern research in the field of control performance assessment (CPA) began when Harris presented the minimum variance benchmark derived from the theoretical background of the minimum variance controller (Harris, 1989). Ever since, a number of methods have been developed for measuring the performance of control loops. However, the approach has been mostly bottom-up: the methods deal with one, or in some cases, multiple control loops performing control of a low-level physical measurable quantity, such as temperature, pressure, or flow.

Industrial processes are usually multivariate, nonlinear and time-varying. The high dimensionality of the data space implies that a human operator will have difficulties when monitoring the process variables: it is very difficult to take into account the interactions between process variables, for example, when trying to determine the reason of unsatisfactory performance.

To alleviate the burden of the operator, features, or performance metrics, can be extracted from the data. A feature can contain in a compressed form information from several process variables, or be a purely computational value of a quantity that cannot be measured directly. Instead of the process variables, the operator will then monitor the features in order to determine the state of the process. As an extreme example, there could be one feature that completely summarized the performance of the system. If the value of the feature changes to an adverse direction, the operator knows that there is a factor that is decreasing the performance of the process.

After an overview of control systems, this section presents some established performance analysis methods. For a more comprehensive review of different metrics, see (Qin, 1998; Qin, 2003; Jelali, 2006). Proprietary software for evaluating controller performance is on the market (Jelali, 2006; Thornhill and Shah, 2005; Trenchard and Boder, 2005), and several industrial applications have been reported (Jelali, 2006; Hägglund, 2005; Jämsä-Jounela *et al.*, 2003; Ahvenlampi *et al.*, 2005; Jelali, 2007; Howard and Cooper, 2009).

## 2.1 Control systems

This section provides a general overview of control systems and defines basic notation to be used in the remainder of the thesis. The main objective of any control system is to make a process to follow a reference in spite of disturbances. The system is often an industrial plant, for example a paper mill, or a part of it, like the speed control of the wire of a paper machine. However, one can use control engineering methods to design and to analyze also nontechnical systems, like biological or economical processes as long as they can be modeled with differential equations. Using differential equations as a model implies that the present states controls of the system affect the future states, i.e. the system is dynamical. The system has always one or several outputs that should have desired values, the references. Disturbances are factors that affect the operation of the system in an unknown and random way. They usually deviate the output from the reference thus weakening the performance of the system.

Going to a more detailed level, a control system is composed of the parts shown in

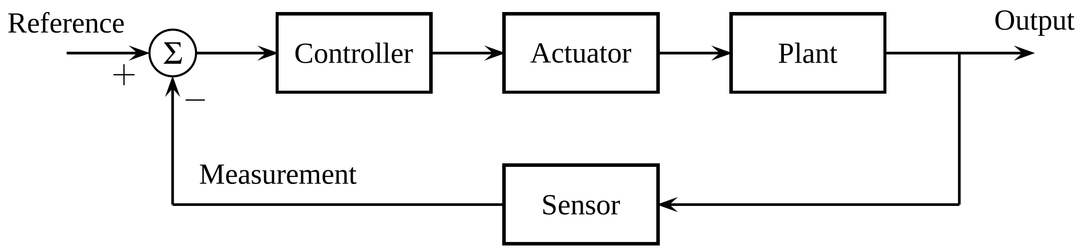


**Figure 2.1:** A control system with feedback.

Figure 2.1. The arrows in the figure represent information flow. The *plant* is the device or the process that is to be controlled and that produces the *output*. The output is *measured* with a *sensor*. Comparing the measured and the *reference* value of the corresponding output gives the *error* signal. The error is fed to the *controller* which is an algorithm that tries to control the plant such that the error becomes zero. Between the controller and the plant there is the *actuator* that interacts physically with the plant as instructed by the controller. Measuring the actual output of the plant and sending this information to the controller, i.e. *feedback*, is a characteristic feature of control engineering. With feedback one can stabilize an unstable plant and correct the errors that have been caused by disturbances.

To give an example, consider the temperature control of an electric sauna (the plant). The temperature of the sauna is measured, and if it is not equal to the reference, say it is too low, the controller decides to turn on the heating elements (the actuator). The measuring of the temperature continues, and once the sauna has reached the desired temperature, the controller turns the heating elements off.

The basic components and structure of a feedback control system can be seen in Figure 2.1. The *transfer function* completely defines the output of a system when the initial state and the input are known. Assuming that the combined transfer function of the controller, the actuator, and the plant is $G(s)$, and that the feedback loop has the unity transfer function (see Figure 2.2), the total transfer function of the feedback system is

$$G_{tot} = \frac{G(s)}{1+G(s)}, \tag{2.1}$$

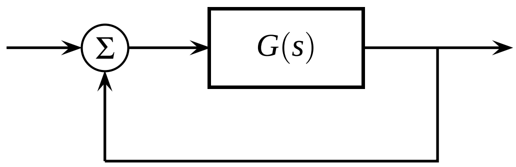


**Figure 2.2:** Simple feedback system with the transfer function $G$ containing the transfer functions of the controller, the actuator, and the plant. The feedback loop has unity transfer function.

where $s$ is the Laplace variable.

In a large-scale process there are usually several simple control loops, each of which controls a specific output. The set points for these controllers can come from another controller which is on a higher level in the control hierarchy. This is illustrated in Figure 2.3 which depicts the different control systems for controlling the altitude of an airplane (Chow and Tipsuwan, 2001). The pilot or the autopilot is the higher-level controller that provides the set points to the elevator, flap and engine controllers in order to change the altitude of the aircraft. Control loops can also be multivariate. If this is the case, at least one of the signals in Figure 2.1 is vector valued so that the system may have, for example, several outputs.

The proportional-integrating-derivative (PID) control structure in transfer function form is

$$G_{PID}(s) = K\left(1 + \frac{1}{T_I s} + T_D s\right), \tag{2.2}$$

where $s$ is the Laplace variable, $K$ the gain of the controller, $T_I$ the integral time, and $T_D$ the derivative time. This structure is used widely in industry. In the refining, chemicals, and pulp & paper industries 97 % of the regulatory controllers use this structure (Desborough and Miller, 2002). The controller can be modified by leaving out some of the terms in the equation, for instance, the proportional-integrating (PI) controller is obtained if the derivative term is omitted.

To complete the section, the following formal definitions are given.

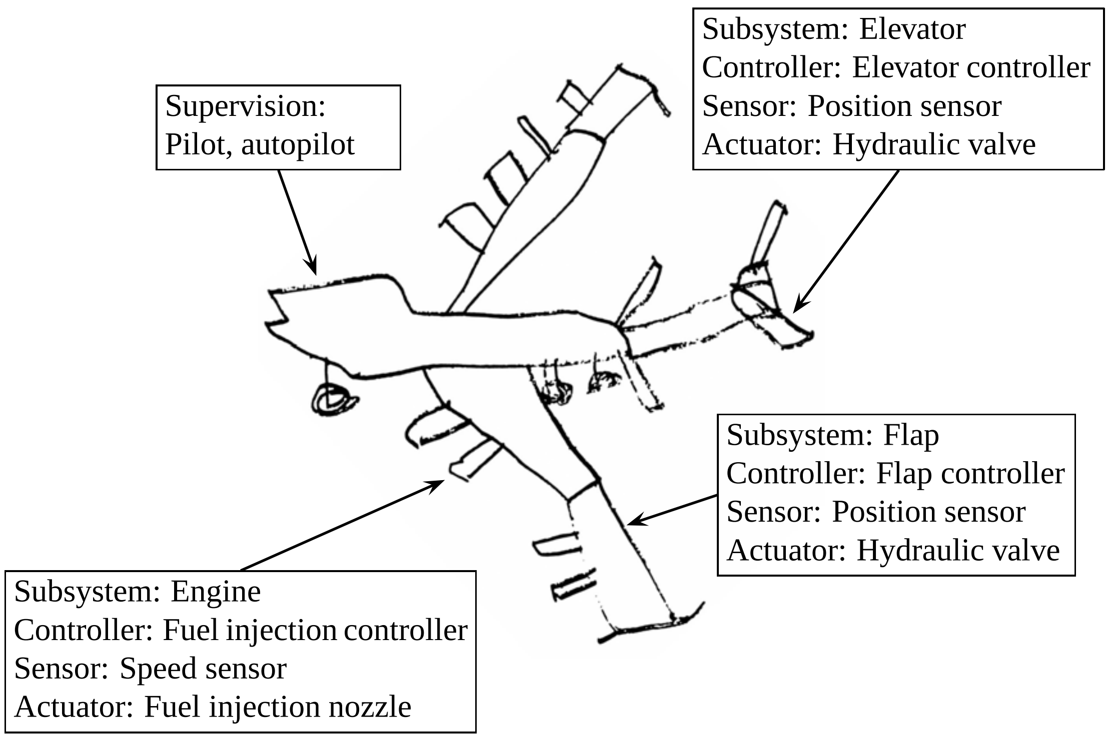


**Figure 2.3:** The different parts of the altitude control system of an airplane. Adapted from (Chow and Tipsuwan, 2001).

- A *process* is a device or a collection of devices intended to transform input substances to output products. An example is the paper manufacturing process, where wood and other raw materials are transformed into paper. Also the term system can be used.

- *Process performance assessment* is the procedure to determine the performance of a given process.

- *Controller performance assessment* is a subset of process performance assessment where the emphasis is on evaluating the performance of the control system of a given process.

- A *performance measure* is a real-valued continuous function $\eta(P, P_0, t, w)$ that describes the performance of the process $P$ with respect to the process $P_0$ at time instant $t$ using parameters $w$. $P_0$ represents usually a process with optimal or otherwise desired performance. The interpretation of a performance measure is not fixed in this definition, i.e. large values of $\eta$ may correspond to good or poor performance, depending on the measure.

- A *performance metric* $H(P, P_0, t, w)$ is a performance measure satisfying the axioms of a metric:

$$
\begin{aligned}
H(P, P_0, t, w) &\geq 0 \text{ (non-negativity)} && (2.3)\\
H(P, P_0, t, w) &= 0 \text{ if and only if } P \text{ and } P_0 \text{ have identical performance} && (2.4)\\
H(P, P_0, t, w) &= H(P_0, P, t, w) \text{ (symmetry)} && (2.5)\\
H(P, P_0, t, w) &\leq H(P, P', t, w) + H(P', P_0, t, w) && (2.6)
\end{aligned}
$$

- A *performance index* $I$ is a performance metric such that $0 < I < 100$. Large values of a performance index imply good performance.

## 2.2 Step response benchmarking

If a controller is to be tuned using trial and error, a straightforward approach is to perturb the process in steady state with a step change in the input signal and then

**Table 2.1:** Step response performance criteria.

| Criterion | Definition |
|---|---|
| Dead time | The time from the change in the input until the effect of the change is seen in the output. |
| Rise time | The time it takes for the output to rise from $y_0 + 0.1\Delta y$ to $y_0 + 0.9\Delta y$ (pictured), or from $y_0$ to $y$. |
| Peak time | The time of the first peak in the output signal. |
| Overshoot | The maximum amount by which the output signal rises above $y_r$. |
| Settling time | The time it takes for the output to remain within e.g. 5 % of $y_r$ |
| Decay rate | The ratio between the sizes of the first and second peaks above the new steady state of the output. |
| Steady-state error | The difference $y - y_r$ when time tends to infinity. |

$y_0$: the initial value of the output signal, $\Delta y$: the size of the change in the output signal induced by the input signal, $y_r$: the new setpoint, $y$: the final value of the ouput signal.

observe the output of the process. Using knowledge about the desired output of the system and the characteristics of the controller, the controller is tuned such that the output is acceptable.

There exist many quantitative criteria to evaluate the performance of a controlled system in the event of a step change to the input or of a load disturbance. Table 2.1 and Figure 2.4 define some possible criteria.

Some of the most used metrics are the integral performance indices derived from the control error, i.e. the difference between the reference signal and the actual output of the system. As an example, the integral of squared error (ISE) criterion is

$$\eta_{ISE} = \int_0^\infty (e(t))^2 dt = \int_0^\infty (y_r(t) - y(t))^2 dt, \tag{2.7}$$

where $e(t)$ is the control error, $y_r(t)$ the reference and $y(t)$ the measured output. In practice, this criterion would be used by introducing a step change to the input of the process at time $t = 0$ and by computing the integral until the error becomes

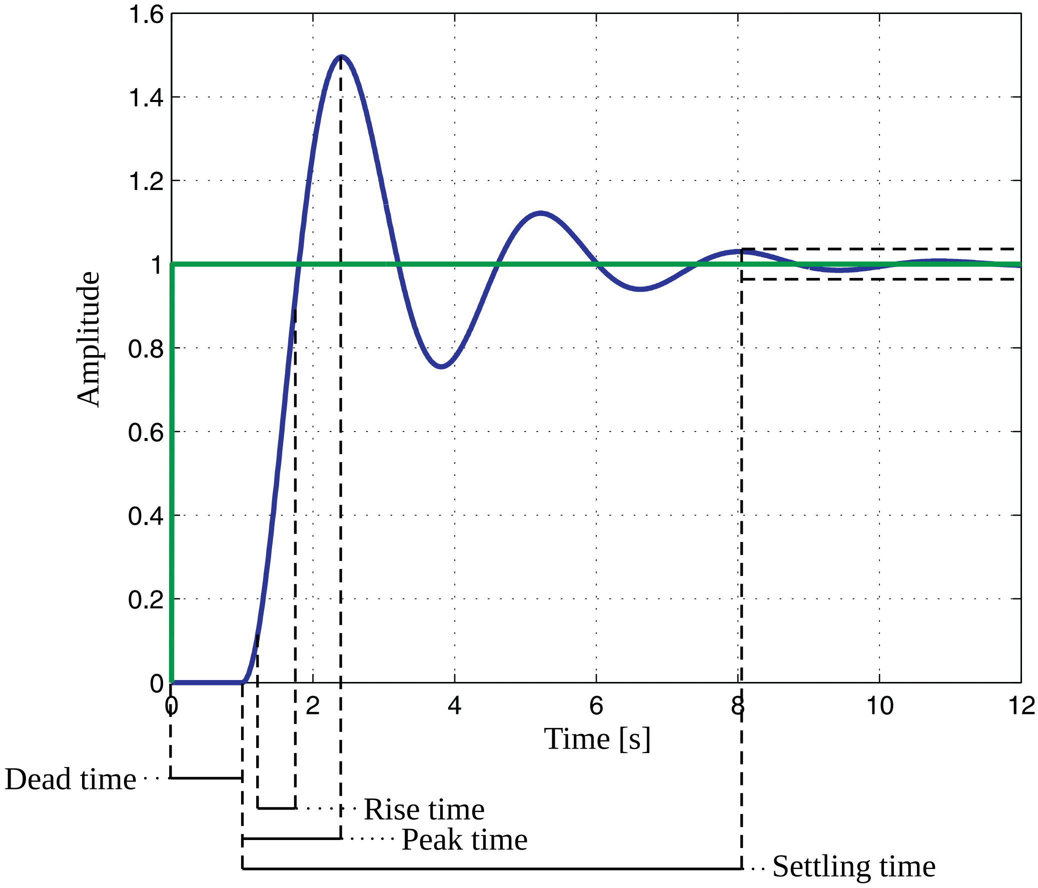


**Figure 2.4:** Step response performance criteria.

close enough to zero (Åström and Hägglund, 1995).

The integral of time-weighted squared error (ITSE) criterion is defined

$$\eta_{ITSE} = \int_0^\infty t(e(t))^2 dt = \int_0^\infty t(y_r(t) - y(t))^2 dt. \tag{2.8}$$

The squared error being multiplied with time $t$, this criterion gives less weight to the inevitable error that occurs immediately after the change in the input, and emphasizes steady-state error.

These criteria can be easily modified to suit different purposes, for example, the square can be replaced with an absolute value, giving the integral of absolute error (IAE) and integral of time-weighted absolute error (ITAE) criteria

$$\eta_{IAE} = \int_0^\infty |e(t)| dt = \int_0^\infty |y_r(t) - y(t)| dt \tag{2.9}$$

$$\eta_{ITAE} = \int_0^\infty t|e(t)|dt = \int_0^\infty t|y_r(t) - y(t)|dt. \tag{2.10}$$

Another useful modification is to take the magnitude of the control signal also into account like in

$$\eta_w = \int_0^\infty w_1(e(t))^2 + w_2(u(t))^2 dt, \tag{2.11}$$

where $u(t)$ is the input signal and $w_1$ and $w_2$ are weights for the error and control signals, respectively. This cost function can be motivated by the facts that control signals often are bounded by physical limitations and that using the control signal has usually a monetary cost. This is the case, for instance, when control means in practice adding some chemical substance to the process. The cost function in (2.11) is a special case of the multivariate quadratic cost function used in linear-quadratic optimal control.

The above criteria are applicable especially in a control loop where the reference input changes often. With these criteria, it is possible to monitor the transient behavior of the control loop, including rise time, overshoot, settling time and steady-state error.

## 2.3 Minimum variance benchmarking

A number of process performance evaluation methods use as a benchmark a stochastic control system with minimum variance control (Åström, 1970). Under minimum variance control, the controller is designed to minimize the variance of the process output. In this section, different minimum variance benchmarks are reviewed after an introduction to minimum variance control.

### 2.3.1 Minimum variance control

Assume that a scalar process can be described using the generic discrete process model (Åström and Wittenmark, 1997; Ordys *et al.*, 2007)

$$A(z^{-1})y(k) = q^{-d}B(z^{-1})u(k) + C(z^{-1})\xi(k), \tag{2.12}$$

where $u(k)$ is the input, $y(k)$ is the output, $\xi(k)$ is a zero-mean disturbance acting on the output, all at discrete time instant $k$, $d$ the delay $(d \geq 1)$, and $A$, $B$ and $C$ are polynomials in the backward shift operator $z^{-1}$ such that

$$\begin{aligned}
A(z^{-1}) &= 1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_{n_A} z^{-n_A} && (2.13)\\
B(z^{-1}) &= b_0 + b_1 z^{-1} + b_2 z^{-2} + \ldots + b_{n_B} z^{-n_B} \qquad b_0 \neq 0 && (2.14)\\
C(z^{-1}) &= 1 + c_1 z^{-1} + c_2 z^{-2} + \ldots + c_{n_C} z^{-n_C}. && (2.15)
\end{aligned}$$

The output at time $k+d$ is obtained by rewriting the process model in (2.12) to the form

$$y(k+d) = \frac{B}{A}u(k) + \frac{C}{A}\xi(k+d). \tag{2.16}$$

An estimate for this can be computed using the Diophantine equation

$$C = AF + z^{-d}G, \tag{2.17}$$

where $F$ and $G$ are polynomials such that

$$\begin{aligned}
F(z^{-1}) &= 1 + \sum_{i=1}^{k-1} f_i z^{-i} && (2.18)\\
G(z^{-1}) &= g_0 + \sum_{i=1}^{n_G} g_i z^{-i}, && (2.19)
\end{aligned}$$

where $n_G = \max(n_C - k, n_A - 1)$. When (2.17) is substituted to (2.16),

$$y(k+d) = \frac{BF}{C}u(k) + \frac{G}{C}y(k) + F\xi(k+d) \tag{2.20}$$

is obtained. Let $\mathcal{E}\{\cdot\}$ denote the expectation operator. Assuming information up to time instant $k$ is available, the variance of (2.20) is

$$\begin{aligned}
\sigma^2 &= \mathcal{E}\left\{y^2(k+d)\right\} && (2.21)\\
&= \mathcal{E}\left\{\left(\frac{BF}{C}u(k) + \frac{G}{C}y(k)\right)^2\right\} + \mathcal{E}\left\{(F\xi(k+d))^2\right\} && (2.22)\\
&= \sigma_0 + \sigma_{MV} && (2.23)
\end{aligned}$$

because the last term in (2.20) is uncorrelated with the two first terms. Due to the fact that $\sigma_{MV}$ is created by a random process, it is impossible to change its magnitude with any predictive action. Hence, to minimize output variance, the term $\sigma_0$ is set equal to zero giving the control law

$$u(k) = -\frac{G}{BF}y(k) \tag{2.24}$$

known as the minimum variance controller.

### 2.3.2 Minimum variance index

Harris (1989) proposed comparing the variance of the controlled variable to the minimum variance control performance. The control law (2.24) is optimal for a process of the form (2.12) in the sense that it minimizes the variance of the process output. In practice this type of a controller is not widely used, for example, because of its excessive use of control effort. However, it is a useful benchmark for other controllers because of the theoretical foundation it is built on.

The minimum variance benchmark can be defined in index form as

$$I = 1 - \frac{\sigma_{MV}^2}{\sigma^2}, \tag{2.25}$$

where $\sigma_{MV}^2$ is the theoretical minimum variance and $\sigma^2$ is the actual variance of the output variable. It can be seen from (2.25) that $0 \leq I < 1$ and that an index value close to zero stands for performance that is close to the performance of the minimum variance controller.

According to Jelali (2006), this index alone can be used to determine if a control loop needs more attention or not: if the Harris index detects no problems, it is not worthwhile to spend more time with the loop. However, it has been shown that for oscillatory control loops, the result given by the Harris index is unreliable (Horch, 2000).

The importance of monitoring the variance can be easily justified: A certain process variable may have a reference value and an interval in which it must stay. If this is not the case, the customer will not accept the product. If the variance of the variable is large or increases, it is difficult to reach the product specification. If it is important that the lower bound is not violated, it may be necessary to increase the reference value in order to guarantee that the process variable stays above the lower bound despite the large variance. Increasing the reference value can lead to an increase in the cost of the raw materials needed for production. However, control loop performance indices based on the minimum variance index monitor only the variance of the controlled variable. It is easy to produce signals with a very different appearance having equal variances.

The value of the minimum variance index can be estimated from process data without solving for the minimum variance controller (Desborough and Harris, 1992; Ordys *et al.*, 2007). Assuming a linear feedback controller

$$u(k) = -C_0 y(k), \tag{2.26}$$

process output obtained from (2.20) is

$$y(k) = z^{-d}\left(\frac{G - BFC_0}{C}\right)y(k) + F\xi(k). \tag{2.27}$$

To obtain an approximate value for the first term in (2.27), it can be replaced with an autoregressive model of length $m$ as in

$$y(k) = \sum_{i=1}^{m} \theta_i y(k-d-i+1) + F\xi(k), \tag{2.28}$$

where $\theta_i$ are the model parameters. Collecting $n$ process output measurements to the matrices

$$y = \begin{bmatrix} y_n \\ y_{n-1} \\ \vdots \\ y_{d+m} \end{bmatrix} \text{ and } X = \begin{bmatrix} y_{n-d} & y_{n-d-1} & \cdots & y_{n-d-m+1} \\ y_{n-d-1} & y_{n-d-2} & \cdots & y_{n-d-m} \\ \vdots & \vdots & \ddots & \vdots \\ y_m & y_{m-1} & \cdots & y_1 \end{bmatrix}, \tag{2.29}$$

and the model parameters to vector $\theta$, the autoregressive model becomes

$$y = X\theta + F\xi. \tag{2.30}$$

Using the least squares estimate of $\theta$, the estimated minimum variance is

$$\sigma_{MV}^2 = \frac{1}{n-d-2m+1}(y - X\theta)^T(y - X\theta), \tag{2.31}$$

and the estimated actual variance is

$$\sigma^2 = \frac{1}{n-d-m+1}y^T y, \tag{2.32}$$

and (2.25) gives the value of the minimum variance index.

### 2.3.3 Multivariate minimum variance index

Since minimum variance control can be generalized for multivariate control, also a multivariate minimum variance index can be formulated (Harris *et al.*, 1996; Huang *et al.*, 2005; Huang *et al.*, 2006; Yu and Qin, 2009).

Assume a multivariate process model of the form

$$y(k) = \mathbf{T}u(k) + \mathbf{N}\xi(k), \tag{2.33}$$

where $y$ and $u$ are the multivariate output and input, respectively, $\mathbf{T}$ and $\mathbf{N}$ are transfer function matrices, and $\xi$ is a vector of random white noise sources with zero mean. Let $\mathbf{D}$ be the interactor matrix of $\mathbf{T}$, i.e.

$$|D| = z^r \text{and} \tag{2.34}$$

$$\lim_{z^{-1}\to 0} \mathbf{DT} = \mathbf{K}, \tag{2.35}$$

where $\mathbf{K}$ is a full-rank constant matrix and $r$ is the number of infinite zeros of $\mathbf{T}$.

The cost criterion corresponding to (2.21) in the multivariate case is

$$\Sigma^2 = \mathcal{E}\left[\tilde{y}(k)^T \tilde{y}(k)\right], \tag{2.36}$$

where

$$\tilde{y}(k) = z^{-d}\mathbf{D}y(k). \tag{2.37}$$

Multiplying both sides of (2.33) by $z^{-d}\mathbf{D}$ yields

$$z^{-d}\mathbf{D}y = z^{-d}\mathbf{DT}u(k) + z^{-d}\mathbf{DN}\xi(k) \tag{2.38}$$

$$= \quad \mathbf{DT}u(k-d)+\mathbf{R}\xi(k-d)+\mathbf{F}\xi(k). \tag{2.39}$$

It is impossible to affect the last term of the above equation with control action. Hence, minimum variance control is achieved by setting

$$\mathbf{DT}u(k-d)+\mathbf{R}\xi(k-d)=0 \tag{2.40}$$

resulting in the control law

$$u(k)=-(\mathbf{DT})^{-1}\mathbf{RF}^{-1}(z^{-d}\mathbf{D})y(k). \tag{2.41}$$

The multivariate minimum variance benchmark can now be defined as

$$\eta=\mathrm{tr}[\mathrm{Cov}(\mathbf{F}\xi(k))]. \tag{2.42}$$

### 2.3.4 Other minimum variance indices

Different modifications of the Harris index have been developed, mostly to relax the assumption of ideal minimum variance control, and to use a more realistic reference for performance. Horch and Isaksson (Horch and Isaksson, 1999) have developed a version of the Harris index where one pole of the system can be placed arbitrarily, and not to the origin as the original Harris index implies. This results in a less aggressive index. The modification by Tyler and Morari (Tyler and Morari, 1996) takes into account performance limits that are caused by non-minimum phase zeros and unstable poles. Also, the non-linear (Harris and Yu, 2007) and time-variant (Huang, 2002) cases have been addressed.

## 2.4 Feature specific performance indices

There exist a number of performance indices that have been developed having a certain desirable or undesirable performance pattern in mind. These include indices for detecting steady-state error, oscillation, sluggish control, etc.

In the case of regulatory control, i.e., the set point is constant, the following permanent error index (PE) can be used (Jämsä-Jounela *et al.*, 2003). The index is calculated recursively while the process is running and a forgetting factor $\gamma$ $(0 < \gamma < 1)$ is used for decreasing the weight that is given to old measurements as in

$$\eta(k) = \gamma\eta(k-1) + (1-\gamma)p(k), \tag{2.43}$$

where

$$p(k) = \begin{cases} -1, & \text{if } e(k) < -e_{lim} \\ 0, & \text{if } -e_{lim} \le e(k) \le e_{lim} \\ 1, & \text{if } e(k) > e_{lim}. \end{cases} \tag{2.44}$$

Here $e(k)$ is the error signal and $e_{lim}$ is the maximum acceptable absolute value for the error. This index converges to zero if the monitored variable differs less than $e_{lim}$ from its set point. Otherwise the value of the index tends to 1 or $-1$ depending on the sign of the error. It is possible to base the selection of the forgetting factor $\gamma$ on the estimated time constant $\tau$ of the process by setting

$$\gamma = 1 - \frac{1}{5\tau}. \tag{2.45}$$

Hägglund (1999) has proposed an index to be used in the detection of sluggish control loops (the sluggish control index, SL) that respond slowly to changes in the output of the system. This index, also known as the idle index, is defined as

$$\eta = \frac{t_{pos} - t_{neg}}{t_{pos} + t_{neg}}, \tag{2.46}$$

where

$$t_{pos} = \begin{cases} t_{pos} + T_s & (\Delta u \Delta y > 0) \\ t_{pos} & (\Delta u \Delta y \leq 0) \end{cases} \tag{2.47}$$

$$t_{neg} = \begin{cases} t_{neg} + T_s & (\Delta u \Delta y < 0) \\ t_{neg} & (\Delta u \Delta y \geq 0) \end{cases}, \tag{2.48}$$

where $T_s$ is the sampling period. The values of this index are, by definition, within the closed interval $-1 \ldots 1$. Values close to zero ($-0.4 < \eta < 0.4$) imply well tuned control, whereas positive values are obtained from sluggish control loops. Negative values ambiguous meaning, and no conclusions regarding the sluggishness of the control loop can be drawn in this case.

For online applications it is possible to use the idle index recursively as in

$$\eta(k) = \gamma\eta(k-1) + (1-\gamma)s(k), \tag{2.49}$$

where $\gamma$ is a forgetting factor and

$$s(k) = \begin{cases} -1, & \text{if } \Delta u \Delta y < 0 \\ 0, & \text{if } \Delta u \Delta y = 0 \\ 1, & \text{if } \Delta u \Delta y > 0 \end{cases}. \tag{2.50}$$

Oscillations are easily generated in feedback control systems by time delays, nonlinear components, and improperly tuned controllers. (Hägglund, 1995; Forsman and Stattin, 1999) propose oscillation detection in a single control loop based on the computation of the IAE between successive zero crossings of the error signal.

In the latter, also general guidelines for the interpretation of the index values are proposed. Also, multivariate oscillation detection has been studied (Tangirala *et al.*, 2005; Xia *et al.*, 2005; Yim *et al.*, 2006).

Other feature specific performance indices include backlash detection (Hägglund, 2007) as well as the process capability index and other measures used in the area of statistical process control (Montgomery, 2005).

## 2.5 High-level benchmarking

In addition to the above-mentioned performance indices that each describe a certain phenomenon, there also exist metrics that relate to the overall performance of a control loop on a general level. Paulonis and Cox (2003) describe a control performance assessment implementation where each control loop is given a score derived from the weighted sum of different low-level performance indices. Xia and Howell (2003) have developed an overall loop performance index, which can give a qualitative description of the performance of a control loop. Their method gives an assessment of loop status among the classes steady, compensated, short-term transient, long-term transient, ultimately cyclic and critical. Each class is connected to a range of values of a performance statistic. Consequently, only one type of performance quality variation can be detected at each time instant.

When compared with the number of publications on performance assessment of individual control loops, there are few papers on combining the assessment results from different sources. A Bayesian approach for combining low-level measures is presented in (Huang, 2007). In (Ahvenlampi *et al.*, 2005) a two-level index hierarchy is documented. Two top-level indices are provided, one describing overall performance and the other the weakest link in the system.

# 3

# Data acquisition and storage for performance evaluation

This chapter discusses different solutions for data acquisition and storage, as well as covers some issues related to data preprocessing.

## 3.1 Data acquisition

The quality of the data sets an upper limit to what can be achieved with performance assessment. Since data acquisition may not be as straightforward as expected, careful planning, charting of different possibilities, and choosing among them is necessary. Usually the data need to be moved from the plant to a software tool that is used for analyzing the data. This means that after the data are accessible, they need to be converted to a format which the analysis software understands. To understand the reasons behind changes in performance, it is insufficient to gather data from the monitored variables: for example, controller parameters and information about the operating conditions are needed (Hägglund, 2005).

There are several practical issues that need to be dealt with: When the data are stored, they can be compressed in different ways, like by removing some measurements, by computing and storing the mean of a given number of measurements, or by storing the measurement only if the measured value changes more than a threshold value. Using compressed data should be avoided because compression has an impact on the results of different data-driven analysis methods (Thornhill *et al.*, 2004). An algorithm to estimate the compression factor from data was presented in (Thornhill *et al.*, 2004), and the authors suggest that it should be used as a standard tool in data preprocessing. Additionally, different variables need not be sampled at the same rate, and the samples may come at different time instants. If there are several different systems storing the data, the synchronization of the clocks of the systems must be checked.

If only a few measurements are needed, it is possible to use a data logger or a computer equipped with an analog to digital converter. These data acquisition devices are connected directly to the process under study. The advantage of this method is that it is possible to choose the sampling rates etc. quite freely. In the case of industrial processes, however, the owner of the process may be reluctant to have additional hardware connected to the process, because they increase the risk of technical problems which may eventually cause a shutdown. If a very high sampling rate is required, this may be the only possible way to gather the data.

If the number of monitored variables is large and if the measurement points are in separate locations, it is impractical and expensive to install devices to log the data. This is especially true as often the data are stored at the plant anyway, reducing the problem of finding an efficient way to access the data.

In a heterogeneous industrial environment, where the process and control system infrastructures may have evolved during a long period of time, the data may be available from different proprietary systems, from a centralized data warehouse, proprietary databases, device-specific log files, among others. All these systems have a different interface for acquiring data, or they may be restricted to viewing and analyzing the data with software by the system provider (Janke, 2000).

Starting from field device level and going to enterprise management level, there are many users for data: intelligent field devices and controllers, distributed control system (DCS), supervisory control and data acquisition (SCADA) systems, data analysis software, manufacturing execution systems (MES), and enterprise resource planning (ERP) systems. It may be possible to export the data in a structured ASCII (ASCII) file that can be imported to the analysis software. If the data are originally in a database, database tools such as the open database connectivity (ODBC) interface and the structured query language (SQL) can be used for accessing the data. These approaches are suitable when data acquisition is done manually for a specific purpose.

In order to connect the different systems directly so that automatic functions and continuous performance assessment would be possible, it was necessary to create a specific driver for each connection pair between devices or software. This resulted in several problems: (Shimanuki, 1999)

1. The number of drivers required was very high leading to excessive developing costs.
2. Drivers were unavailable for all connection pairs.
3. Conflicts between drivers caused some hardware features to be unavailable.
4. Changes in hardware caused driver failures.
5. Simultaneous access to a device was difficult or impossible.

To solve these problems, several general-purpose data exchange interface standards have been developed, including OPC, common object request broker architecture (CORBA), COM/DCOM, and remote method invocation (RMI). Software conforming to a standard will be able to communicate, at least to some extent, with all other compliant software applications. For usage examples of these data exchange interfaces, see (Liu *et al.*, 2005; Thornhill and Shah, 2005).

## 3.2 Data storage

Once the data are obtained, it may be useful to store it in a database that has been specifically designed for analyzing the data. This is the case especially when the data come from different data sources in different formats. Even if there is only one data source, storing the data to be analyzed in a distinct research database is wise if the interesting variables are only a small subset of all available variables. Also, if the data require extensive preprocessing, it is beneficial to store the preprocessed data to remove the need to preprocess the same data again and again.

## 3.3 Data preprocessing

It is important not to use the data obtained from an industrial process directly without preprocessing. Data usually have different erroneous features which will lead to incorrect decisions if they are not filtered from the data. Exceptional events during operation, programming errors and measurement errors can produce measurements that are completely erroneous, and can differ by several orders of magnitude from the correct range of the variable. This section addresses certain details that need to be taken into account when the data are prepared for analysis. For more information, see the work by (Pyle, 1999).

In the following different phenomena that are often seen in data are presented. In Figure 3.1 the measured variable has three step changes and remains at the same level between the step changes. The different levels correspond to different operating points of the process, for example, different production rates. If the process is linear, the operating point has no effect on the dynamics of the process. However, most industrial processes are nonlinear. For nonlinear processes, the operating point must be taken into account by using it as an input variable when the data are modeled, or by constructing different models for each operating point. If the information of the operating point is neglected, the changes in the performance indices reflect mostly changes in the operating point (Hietanen *et al.*, 2005).

Data can contain missing values represented by a timestamp-value-pair that is missing altogether, or a zero or infinite value, or a nonzero constant value. Usual reasons for missing data include broken sensors or other hardware, or hardware that has been removed or was never installed. It is also possible that the data were lost while transmitting or storing them in a database.

Incorrect values that are not missing data are outliers. They can be further divided into obvious and non-obvious outliers (Qin, 1997). Obvious outliers have values that are outside the physical limits of the system, for instance, it is impossible for a tree length to be in the range of kilometers. These outliers can be successfully eliminated using process knowledge to set limiting values for each measurement. Figure 3.2 shows a variable that has, in addition to ordinary measurement noise, randomly occurring non-obvious outliers of changing magnitude. The outliers can be caused, for example, by electromagnetic disturbances to the measurement circuit. By visual inspection of the data it is plausible that the anomalous values are outliers, but in principle they could be correct values produced by the system. If it is impossible to eliminate the source of the disturbances, filtering is needed to remove the erroneous measurements. The outliers in Figure 3.3 are due to an automatic sensor washing sequence which is repeated hourly. To detect this type of problems in the data, process knowledge is needed. In most cases it is necessary to co-operate with representatives of the plant to reliably screen out errors of this type.

## 3.4 Discussion

The selection of the data acquisition method is application dependent. This is, however, an important step in a performance assessment implementation, since the amount and quality of data sets an upper limit for the usefulness of the entire performance assessment system. Proper storage ensures easy access to the data for

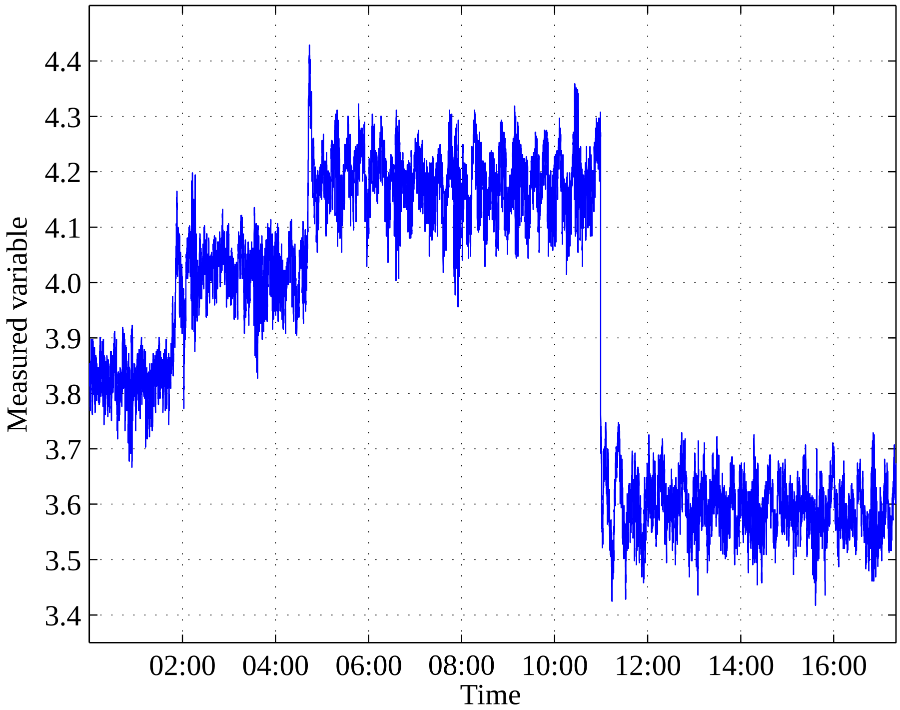


**Figure 3.1:** The process has three different operating points.

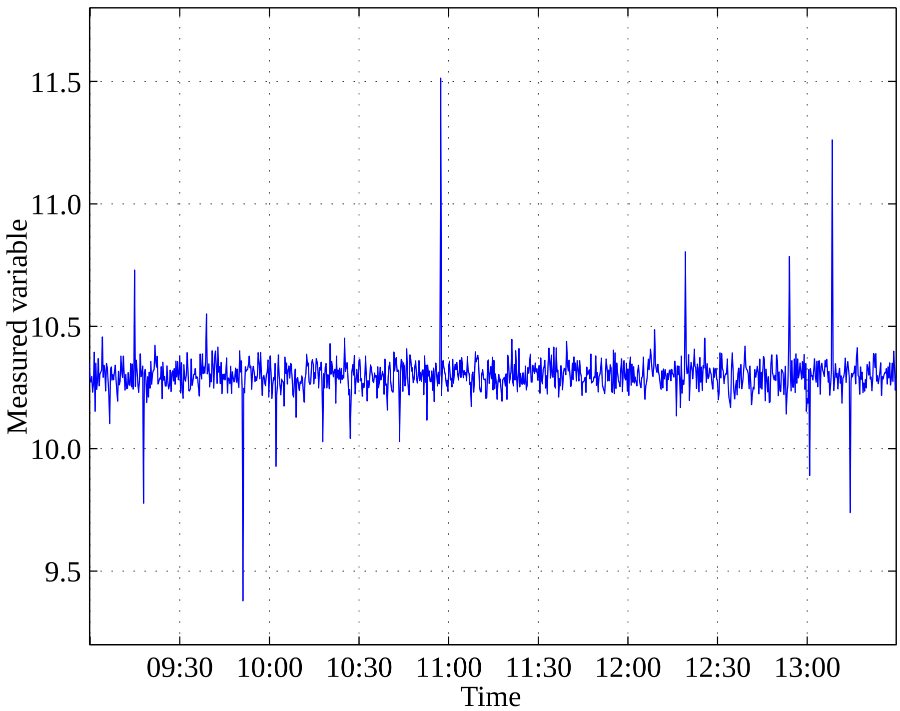


**Figure 3.2:** The measurement has individually occurring outliers.

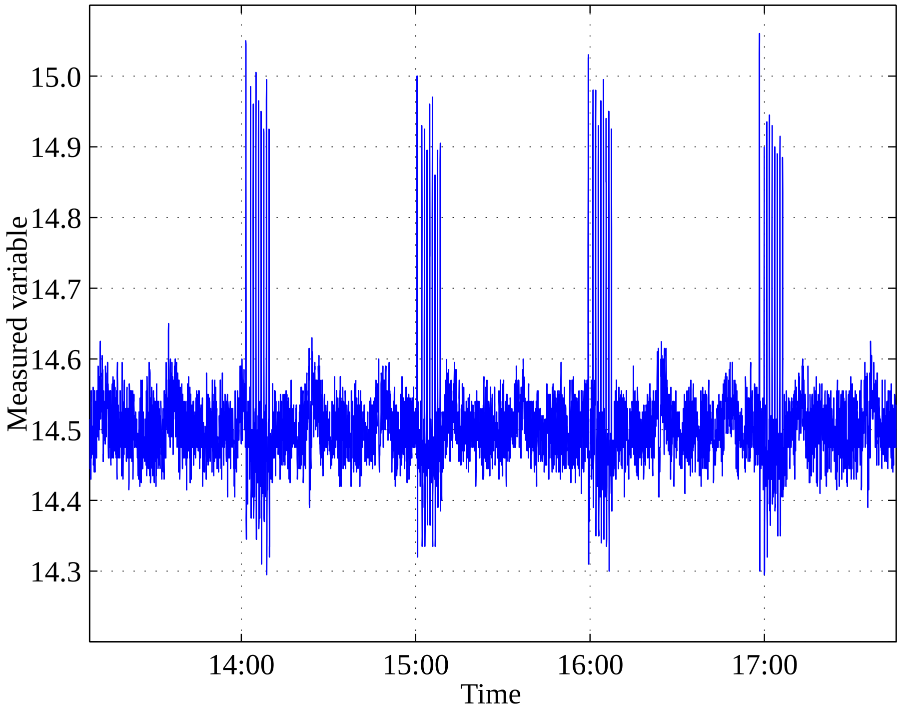


**Figure 3.3:** Periodic disturbance due to automatic sensor washing sequence.

all current and future usages. It is also important to study the outlier types in the different variables of the dataset, as well as to find different operating points that need to be taken into account in performance assessment. Improper preprocessing of the data may lead into the failure of the performance assessment system if outliers, operating point changes, and other external factors are interpreted as changes in performance, and mask true performance variations.

# 4 Performance measures for two-dimensional web processes

Traditional performance metrics concentrate on one-dimensional measurements. In this chapter, two-dimensional web processes that can be found, for instance, in paper, plastic film and steel manufacturing are presented. Then several novel indices are proposed to be used in evaluating the performance of two-dimensional web processes.

In a two-dimensional web process the product is a planar object being relatively thin when compared to the width and the length of the object. The direction of product movement is called the machine direction (MD), whereas the direction perpendicular to the MD is the cross direction (CD). Material flow is provided to the headbox, which is responsible of distributing the material in the cross direction. Devices exist to move the material in the machine direction. Because of the configuration of the web process, the CD and MD are also called the spatial and temporal dimensions, respectively.

As a result of the different physical configuration of the paper machine in CD and MD directions, the dynamical properties of the product in CD and MD directions tend to be unalike: the variations in the MD are due to variations, e.g., in the input to the headbox, whereas the variations in the CD are caused for instance by the headbox and the calenders. An example in Figure 4.1 illustrates the differences

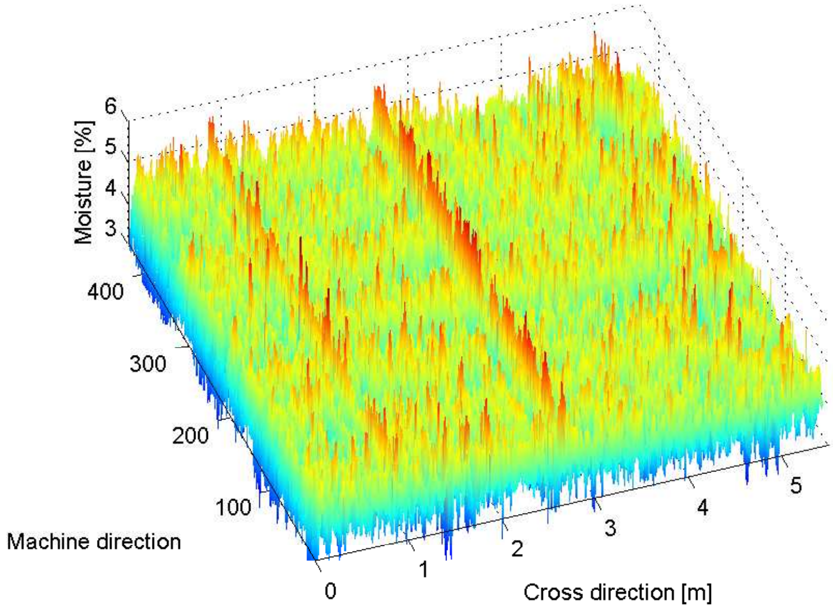


**Figure 4.1:** Raw measurement data (moisture) from a paper machine showing the different nature of CD and MD dynamics.

between CD and MD dynamics. Although corrupted by measurement noise, the overall profile in the CD remains the same. In the CD, however, there are fast variations in the measurements.

Figure 4.2 illustrates a measurement arrangement that uses a scanner traversing the web with constant speed. Since the web travels in the MD, the path of the scanner with respect to the web is of zig-zag shape. There exist also measurement arrangements that use a variable-speed scanner to improve accuracy, and full-web width scanners that measure the entire CD simultaneously.

Because of the zig-zag movement of the scanner, the raw profiles are a combination of three components: (Kristinsson and Dumont, 1996)

- *The machine direction (MD) component.* Variations occurring along the sheet travel direction of the machine and affecting the whole width of the machine. MD variations are expected to affect the whole width of the sheet similarly.
- *The cross-direction (CD) component.* Variations occurring perpendicularly

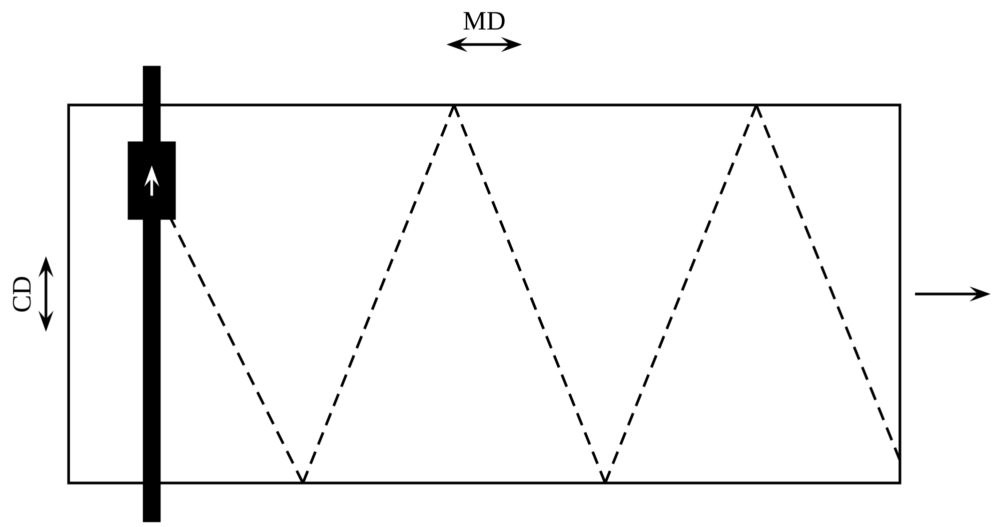


**Figure 4.2:** CD and MD measurements.

to the sheet travel direction of the machine. Generally speaking, CD variations are slower than MD variations, and can be assumed to be nearly time-invariant. CD variations will persist in successive profiles.

- *The random component.* Random variations that occur neither along nor across the machine. These variations are due to measurement noise etc.

The process of separating the MD, CD, and residual components is referred as CD-MD separation. The problem that needs to be addressed in CD-MD separation is that certain pure CD variations, pure MD variations and variations that are a function of both CD and MD position, produce the same signal when measured with a traversing scanner (Taylor, 1991; Duncan and Wellstead, 2004). The separation is necessary because the control system will correct variations in a different manner whether they are CD or MD variations by origin. Literature related to CD-MD separation includes (Taylor, 1991; Dumont *et al.*, 1993; Wang *et al.*, 1993; Balderud and Wilson, 2001).

In the following sections, several performance indices for two-dimensional web processes are proposed. It is assumed that constant-speed scanner measurements are available, sampled in the CD and the MD evenly in the time domain. The sampling rates in CD and MD need not to be the same. Denote the measurements with $p(k,i)$, where $k$ and $i$ are positive integers indicating the temporal and spatial locations of the sample. The index $i \le N$, where $N$ is the number of samples in the CD. The vector of all CD measurements taken at a given pass of the scanner is denoted with $p(k)$ and is known as the profile of the web. When necessary, the CD-MD separation method presented in (Dumont *et al.*, 1993; Wang *et al.*, 1993) is used.

## 4.1 Variation in machine direction

This index measures variation in machine direction by computing the standard deviation of the mean of each profile.

Parameter:

- $\lambda$: forgetting factor.

Inputs:

- The mean $\mu(k)$ of the MD component values corresponding to one profile.
- The previous exponentially smoothed mean $\bar{\mu}(k-1)$.
- The previous index value $\bar{\sigma}(k-1)$.

Algorithm:

1. Compute the exponentially smoothed mean using
$$\bar{\mu}(k) = \lambda\bar{\mu}(k-1) + (1-\lambda)\mu(k). \tag{4.1}$$
2. Compute the exponentially smoothed variance
$$\bar{\sigma}^2(k) = \lambda\bar{\sigma}^2(k-1) + (1-\lambda)(\bar{\mu}(k) - \mu(k))^2. \tag{4.2}$$
3. Compute the index value using
$$\eta = \sqrt{\bar{\sigma}^2(k)} = \bar{\sigma}(k). \tag{4.3}$$
4. Return $\eta$.

## 4.2 Two-dimensional minimum variance

While the previous index operates on the MD data, this index uses the original measurements to account for the entire width of the machine.

Parameters:

- $d$: dead time in samples.
- $n$: size of the dataset.
- $m$: length of the autoregressive model.

Input:

- Previous $n$ profile vectors with no CD-MD separation.

Algorithm:

1. Estimate the parameters of the autoregressive model in (2.30) for each point $i$ in the profiles.
2. Compute the estimates for the minimum variance $\sigma^2_{i,MV}$ (Equation (2.31)) and the actual variance $\sigma^2_i$ (Equation (2.32)) for each point $i$ in the profiles.
3. Compute the index value using (Ettaleb, 1999)
$$\eta = \frac{\sum_{i=1}^{p} \sigma^2_{i,MV}}{\sum_{i=1}^{p} \sigma^2_i}. \tag{4.4}$$
4. Return $\eta$.

## 4.3 Shape of the profile

With this index it is possible to find variations of a certain size from the profiles. It takes into account the features that are narrower than $l_1$ meters and wider than $l_2$ meters. The algorithm consists of two filtering steps. First, variations wider than $l_1$ are filtered out. The filtered profile is then subtracted from the zero-centered profile, and the result is filtered to remove variations narrower than $l_2$. Both filtering operations are performed using the median filter in order to avoid smoothing the edges of sharp changes in the profile as would be the case with mean-like filtering.

Parameters:

- $N$: the nominal number of measurement points in the profile.
- $L$: the width of the machine.
- $l_1$: upper threshold for variation size.
- $l_2$: lower threshold for variation size.

Input:

- One profile vector $p$, CD component.

Algorithm:

1. Compute $\mu = p - \text{median}(p)$ to set the median of the profile equal to zero.
2. To obtain the profile $s$ with variations wider than $l_1$ filtered, apply median filter (see Appendix A) to $\mu$ using the window size
$$w_1 = 2 \text{ round}\left(\frac{l_1 N}{L}\right) + 1. \tag{4.5}$$
3. To obtain the profile $r$ with variations wider than $l_1$ and narrower than $l_2$ filtered, apply median filter (see Appendix A) to $\mu - s$ using the window size
$$w_2 = 2 \text{ round}\left(\frac{l_2 N}{L}\right) + 1 \tag{4.6}$$
to obtain $r$ (see Appendix A).
4. Compute the index value using
$$\eta = \frac{1}{N}\sum_{i=1}^{N} r^2, \tag{4.7}$$
5. Return $\eta$.

Figure 4.3 illustrates the principle of the algorithm. In the upper part of the figure, the original profile with the mean subtracted is shown, as well as the filtering results from steps 2 and 3 of the algorithm. Profile $r$ is repeated in the lower part of

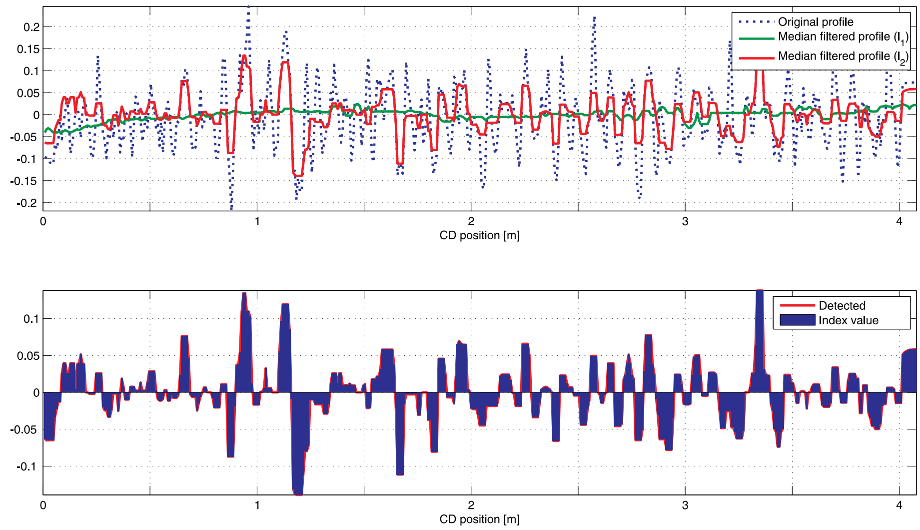


**Figure 4.3:** Example of the computation of the shape index.

the figure with the shaded area between $r$ and 0 being proportional to the value of the index.

Depending on the values of the parameters $l_1$ and $l_2$, this method can be used to detect different anomalies in the shapes of the profiles. It is possible to define several performance indices with different parameters, each monitoring a certain range of variation sizes. As a special case, setting $l_1 = \infty$ results $s$ being indentically zero, and the method evaluates the overall shape of the profile.

## 4.4 Duration of set point error

This index evaluates the set point tracking with emphasis on the duration of the tracking error and is based on the set point error index presented in (Jämsä-Jounela *et al.*, 2003). The longer the measurement deviates from the set point, the poorer the index value becomes. The magnitude of the error is ignored.

The index uses exponential filtering to give less emphasis to older measurement values. The filtering rate is controlled using the forgetting factor $\gamma$ $(0 < \gamma < 1)$.

The value of the index converges to 1 if the tracking error is within the acceptable region, and to 0 otherwise.

Parameters:

- $y_r$: set point.
- $\gamma$: forgetting factor.
- $e_{lim-}$: lower bound of the acceptable region.
- $e_{lim+}$: upper bound of the acceptable region.

Inputs:

- The index value $\eta(k-1)$ for the previous profile
- One profile vector with no CD-MD separation.

Algorithm:

1. Compute the mean $\mu$ of the profile $p$.
2. Compute the tracking error $e = y_r - \mu$.
3. Assign
$$i = \begin{cases} -1, & \text{if } e < -e_{lim-} \\ 0, & \text{if } e_{lim-} \leq e \leq e_{lim+} \\ 1, & \text{if } e > e_{lim+} \end{cases} \tag{4.8}$$
4. Compute
$$I(k) = \gamma I(k-1) + (1-\gamma)i, \tag{4.9}$$
5. Compute the index value using
$$\eta = |I(k)|. \tag{4.10}$$
6. Return $\eta$.

## 4.5 Magnitude of set point error

This index evaluates the set point tracking with emphasis on the magnitude of the tracking error. The larger the deviation from the set point, the poorer the index value becomes. The duration of the error is ignored.

The parameters, inputs and algorithm of this index are identical to the set point error duration index except for (4.8) which becomes

$$i = \begin{cases} -(e+e_{lim-})^2, & \text{if } e < -e_{lim-} \\ 0, & \text{if } e_{lim-} \leq e \leq e_{lim+} \\ (e-e_{lim+})^2, & \text{if } e > e_{lim+} \end{cases} \tag{4.11}$$

## 4.6 Difference

This index evaluates the difference of two measurements. It is intended especially for measuring the difference between two variables.

Inputs:

- Most recent profile vectors of two measurements ($p_1$, $p_2$), CD component.

Algorithm:

1. Compute the index value using

$$\eta = \frac{1}{N}\sum_{i=1}^{N}(p_1(i) - p_2(i))^2, \tag{4.12}$$

where $N$ is the number of valid measurements in the vectors and $p(i)$ is the $i^{th}$ element of the measurement vector.

2. Return $\eta$.

## 4.7 Discussion

In this chapter, a number of performance measures for two-dimensional web processes were proposed. To illustrate how the measures can be used in performance assessment, Figure 4.4 shows a set of moisture profile data from a paper machine together with the values of performance indices. For a complete description of a large-scale implementation see Chapter 8. To show the long-term behavior of the indices, six fragments of data with an interval of one month were picked. The length of each fragment is about 200 minutes. The left side of the figure contains the CD profile data, and the graphs on the right show the values of four performance indices for the profile data. The direction of time is downwards. For each performance index, a value close to 100 is desirable.

The list of algorithms presented is not exhaustive: it is possible to modify the proposed algorithms and to develop new ones. Median filtering was selected in several algorithms instead of using the mean in order to have a faster response to step changes in the CD. In some applications the mean, or frequency domain filtering, might be more appropriate.

The measurement setup that was used in this chapter is typical in the paper industy, where the metrics are readily applicable. Selecting this measurement setup does not limit the applicability of the metrics since it is sufficient to provide the metrics with data that indicate CD and MD behavior.

The algorithms presented in this chapter were designed to capture variations that occur particularily in paper production, and have shown to be valid in detecting them. There is, however, no fundamental limitation for applying the performance indices in other industries also. The validity of each algorithm must be verified separately for each application because of the different properties and performance requrements of different applications.

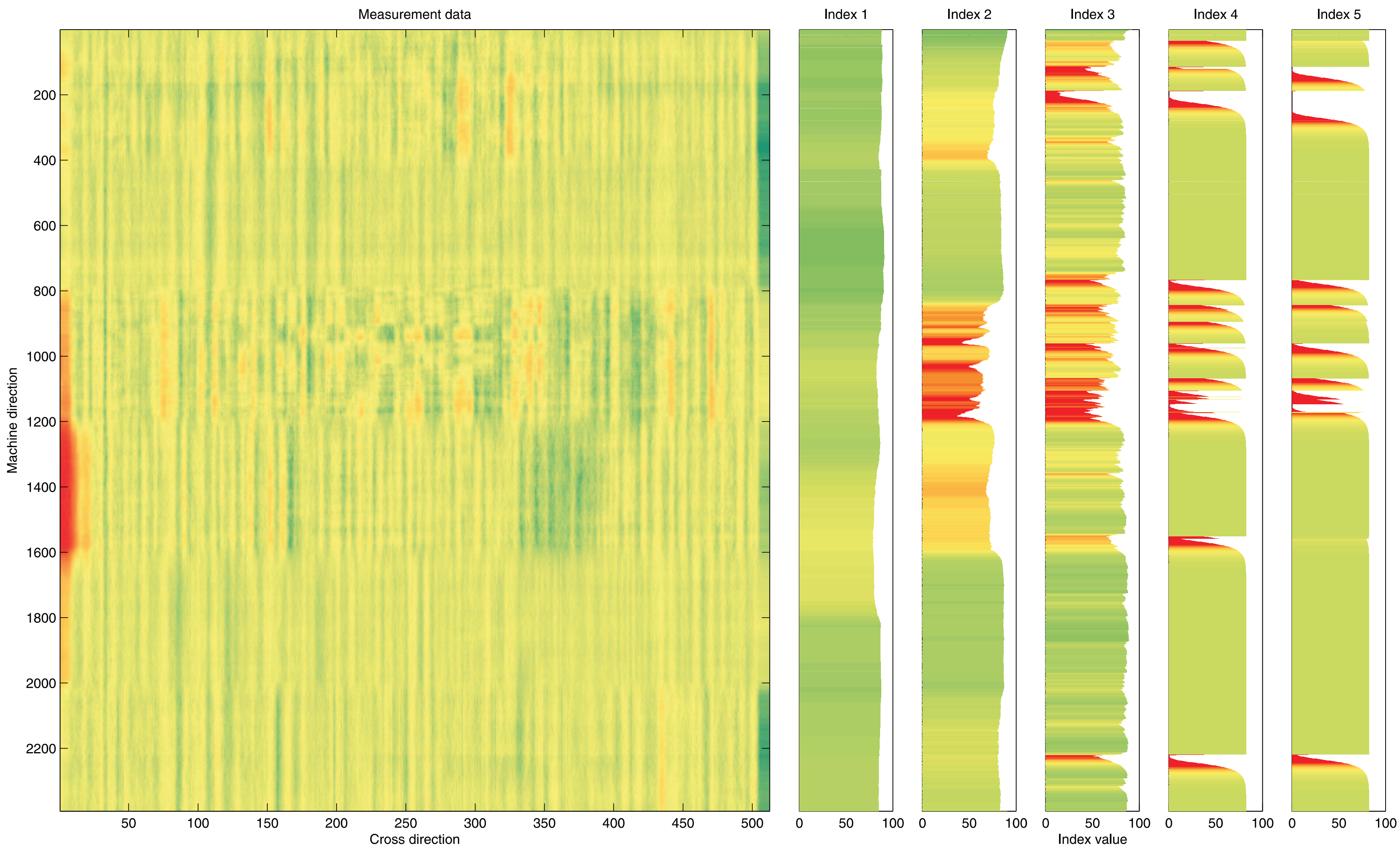


**Figure 4.4:** Examples of the indices. Left: profile data, right: two-dimensional minimum variance, shape, variation, duration of set point error, and magnitude of set point error indices.

# 5 Normalized performance indices

In this chapter, a method is proposed for scaling different performance indices such that they can be easily and intuitively compared to each other.

There are obviously several possible methods to map the measured values to the interval $0 \ldots 100$. In this chapter, two methods are proposed for scaling different performance indices such that they can be easily and intuitively compared to each other.

The original minimum variance performance index as defined by Harris (1989) is interpreted such that values close to 0 correspond to good behavior, and the larger the index value is, the more performance has deteriorated. Generally speaking, control loop performance indices can have arbitrary values belonging to intervals determined by their definitions. For some indices, small values represent good performance, whereas the contrary applies to others. This is often the case in practice, when each device in the plant comes with a specific fault diagnosis module, each of which is using a different scheme and different outputs for performance monitoring. Consequently, it is difficult to compare the values of the indices because of their different scales and variances.

To be able to easily compare and combine the different indices, they must be scaled to the same interval. For example, the authors in (Huang *et al.*, 1997*a*; Huang *et* *al.*, 1997*b*) suggest using indices that are scaled to, or by definition produce values that are within the closed interval $0 \dots 1$, where 1 corresponds to better performance. Jelali (2006) justifies this with the widespread usage of this definition. This selection is in close relation with fuzzy logic, where the degree of membership to a certain class is represented with a value in the closed interval $0 \dots 1$.

In order to further ease the interpretation and usage of different quality indices, scaling to the open interval $0 \dots 100$ is suggested in this thesis. For human beings, it seems to be more intuitive to use integer values, and it is sufficient to present the integer part of a scaled index to the user. Moreover, the value 100 signifying the best performance possible, i.e. 100 % performance, is very intuitive also for persons with less mathematical training. Automatic monitoring can use also the non-integer part of the indices, and the openness of the interval provides additional advantages that will be discussed later.

## 5.1 Continuously differentiable scaling functions

In this section, the following continuously differentiable scaling functions for different types of performance indices are proposed (Hölttä and Koivo, 2009). In each case the basic function shape is the same in order to have scaling functions with similar properties. The scaling functions were selected such that they are continuously differentiable. Smoothness of the scaling function eases the use of the scaled performance index values as cost functions in optimization. Additionally, the scaling functions tend asymptotically to their minimum and maximum values. Consequently, the scaling functions have inverse functions, which can be used to convert the scaled indices to unscaled ones if necessary.

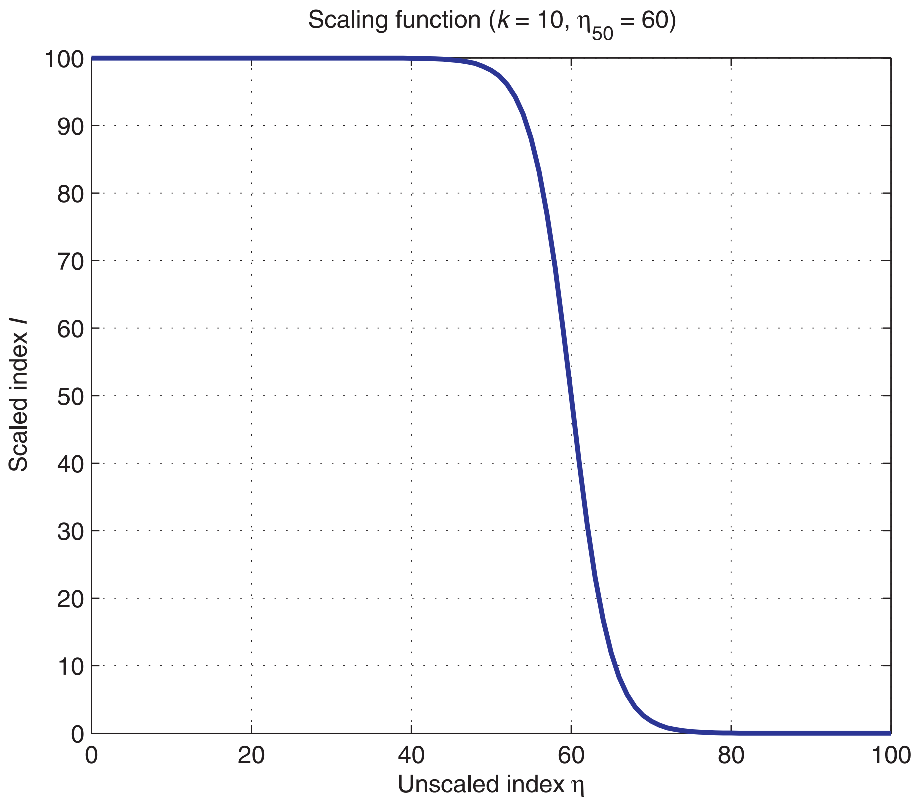


**Figure 5.1:** A decreasing scaling function.

### 5.1.1 Decreasing scaling function

In the case where the performance measure is defined such that small index values represent good behavior, the scaling function is proposed to be

$$I = f(\eta) = \frac{100}{1 + e^{-\frac{k}{25}(\eta_{50} - \eta)}}, \tag{5.1}$$

where $\eta$ is the unscaled and $I$ the scaled performance index. The interpretation of the parameters $k$ and $\eta_{50}$ is as follows: Evaluating (5.1) at $\eta = \eta_{50}$ gives

$$f(\eta_{50}) = 50. \tag{5.2}$$

Differentiating (5.1) gives

$$\frac{d}{d\eta} f(\eta) = \frac{-4ke^{-\frac{k}{25}(\eta_{50}-\eta)}}{\left(1+e^{-\frac{k}{25}(\eta_{50}-\eta)}\right)^2}. \tag{5.3}$$

Evaluating (5.3) at $\eta = \eta_{50}$ gives

$$\frac{d}{d\eta} f(\eta_{50}) = -k. \tag{5.4}$$

Hence, the parameters $k$ and $\eta_{50}$ of the scaling function in (5.1) are the slope of the scaling function at $\eta = \eta_{50}$ and the unscaled index value corresponding to scaled index value 50, respectively. See Figure 5.1 for an example of a decreasing scaling function.

### 5.1.2 Increasing scaling function

In the case where the performance measure is defined such that large index values represent good behavior, the scaling function is proposed to be

$$I = f(\eta) = \frac{100}{1+e^{\frac{k}{25}(\eta_{50}-\eta)}}, \tag{5.5}$$

where $\eta$ is the unscaled and $I$ the scaled performance index. Figure 5.2 illustrates this scaling function. The parameters have a similar interpretation as in (5.1), but the slope is now $k$.

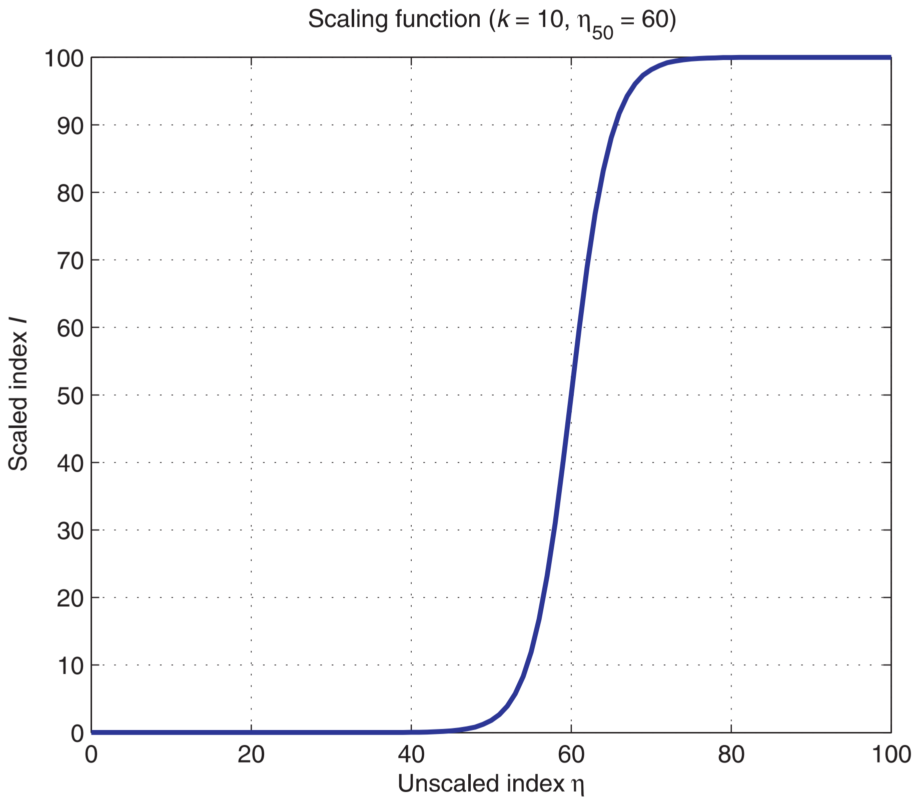


**Figure 5.2:** An increasing scaling function.

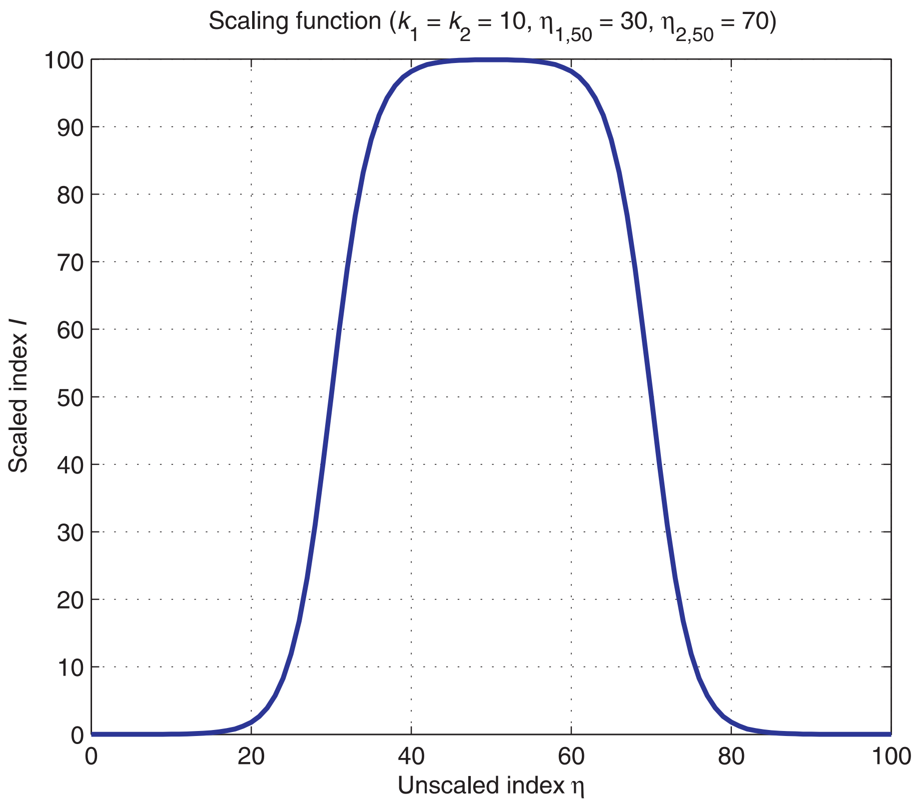


**Figure 5.3:** A bell-shaped scaling function.

### 5.1.3 Bell-shaped scaling function

In the case where the desired values of the performance measure are around a mean value, the scaling function is proposed to be

$$I = f(\eta) = \frac{100}{\left(1 + e^{\frac{k_1}{25}(\eta_{1,50} - \eta)}\right)\left(1 + e^{-\frac{k_2}{25}(\eta_{2,50} - \eta)}\right)}, \tag{5.6}$$

where $\eta$ is the unscaled and $I$ the scaled performance index. This scaling function is illustrated in Figure 5.3 and it results in a bell-shaped curve. The first term of the product in the denominator of (5.6) represents the increasing part of the scaling function, and the latter represents the decreasing part. The scaling parameters $k_i$ and $\eta_i$ have the same qualitative interpretation as in scaling functions (5.1) and (5.5), but the properties (5.2) and (5.4) only hold approximately.

### 5.1.4 Alternative parametrizations of the scaling functions

If it is more convenient to fix an unscaled index value corresponding to an arbitrary scaled index value $I$, it is possible to substitute $\eta_{50}$ in (5.1) with

$$\eta_{50} = \eta_I \mp \frac{25 \ln\left(\frac{100-I}{I}\right)}{k}, \tag{5.7}$$

where the minus or plus sign is to be selected for the decreasing (Equation (5.1)) or increasing (Equation (5.5)) case, respectively. If e.g. $I = 90$, we obtain for the decreasing case

$$\eta_{50} = \eta_{90} + \frac{50 \ln 3}{k}. \tag{5.8}$$

If it is more convenient to fix two unscaled index values instead of the slope of the scaling function, the parameters $k$ and $\eta_{50}$ can be substituted with

$$
\begin{aligned}
k &= \frac{25\ln\left(\frac{I_2(I_1-100)}{I_1(I_2-100)}\right)}{\eta_{I_1}-\eta_{I_2}} && (5.9)\\
\eta_{50} &= \eta_{I_2} - \frac{25}{k}\ln\left(\frac{100-I_2}{I_2}\right), && (5.10)
\end{aligned}
$$

where the scaled index values $I_1$ and $I_2$ correspond to the unscaled values $\eta_{I_1}$ and $\eta_{I_2}$, respectively. This parametrization holds for the decreasing case, i.e. $I_1 > I_2$ and $\eta_{I_1} < \eta_{I_2}$. For the increasing case, the parameters are

$$
\begin{aligned}
k &= \frac{25\ln\left(\frac{I_1(I_2-100)}{I_2(I_1-100)}\right)}{\eta_{I_1}-\eta_{I_2}} && (5.11)\\
\eta_{50} &= \eta_{I_1} + \frac{25}{k}\ln\left(\frac{100-I_1}{I_1}\right). && (5.12)
\end{aligned}
$$

### 5.1.5 Selection of scaling function parameters

Scaling function parameters can be selected using process knowledge or based on data. In the simplest case, it is sufficient for an application area expert to give a limit for acceptable behavior corresponding to, for example, the scaled index value 90 (cf. (5.8)) and the rate at which the scaled index value should decrease (cf. (5.4)). This information may already exist in the form of alarm limits.

When tuning the parameters based on data, a suitable criterion is needed. Using, for instance, the standard deviation $\sigma$ of an unscaled performance index, one could set for the decreasing case

$$
\begin{aligned}
\eta_{90} &= \mu + 2\sigma && (5.13)\\
\eta_{10} &= \mu + 3\sigma, && (5.14)
\end{aligned}
$$

where $\mu$ and $\sigma$ are the mean and the standard deviation of the unscaled performance index, respectively. This selection results in having the performance index values less than $\mu + 2\sigma$ scaled to values greater than 90, and values greater than $\mu + 3\sigma$ scaled to values less than 10.

### 5.1.6 Inverse scaling functions

In order to remove the effect of scaling, the inverse scaling functions are needed. The inverse of the decreasing scaling function (5.1) is

$$\eta = \frac{25}{k} \ln\left(\frac{100 - I}{I}\right) + \eta_{50}. \tag{5.15}$$

The inverse of the increasing scaling function (5.5) is

$$\eta = -\frac{25}{k} \ln\left(\frac{100 - I}{I}\right) + \eta_{50}. \tag{5.16}$$

No inverse exists for the bell-shaped scaling function (5.6). If the possibility to unscale is to be retained, this can be achieved, for example, by storing a binary variable that indicates whether the unscaled index was located in the increasing or the decreasing part of the scaling function.

## 5.2 Piecewise linear scaling function

Before the scaling functions described earlier were developed, a piecewise linear scaling function was used (Hölttä *et al.*, 2005; Hölttä, 2005).

In this approach the normalized performance indices are computed as follows. First lower and upper bounds, $\alpha$ and $\beta$, respectively, are defined for each unscaled index. In a case where larger measured values represent better performance, the coefficients

$$k = \frac{100}{\beta - \alpha} \tag{5.17}$$

$$b = -\frac{100\alpha}{\beta - \alpha} \tag{5.18}$$

are computed. If smaller index values are better, the coefficients

$$k = -\frac{100}{\beta - \alpha} \tag{5.19}$$

$$b = \frac{100\beta}{\beta - \alpha} \tag{5.20}$$

are used instead. The scaled index is then computed as

$$\tilde{I} = \begin{cases} \frac{8}{5}(k\eta + b), & \text{if } \eta \leq \frac{\alpha+\beta}{2} \\ \frac{2}{5}(k\eta + b) + 60, & \text{if } \eta > \frac{\alpha+\beta}{2}. \end{cases} \tag{5.21}$$

where $\eta$ is the unscaled index. As the values of $\tilde{I}$ may be less than 0 or greater than 100, the obtained index value is then limited to the closed interval $0 \ldots 100$ with a hard limit

$$I = \min(\max(\tilde{I}; 0); 100). \tag{5.22}$$

Figure 5.4 illustrates the piecewise linear scaling function in a case where larger measured values represent better performance. The figure shows that the lower bound for the measurement $\alpha$ maps to the scaled index value 0, and the upper bound $\beta$ to the value 100. The mean of $\alpha$ and $\beta$ maps to 80. This scaling function has no inverse due to the fact that values less than 0 and greater than 100 are truncated.

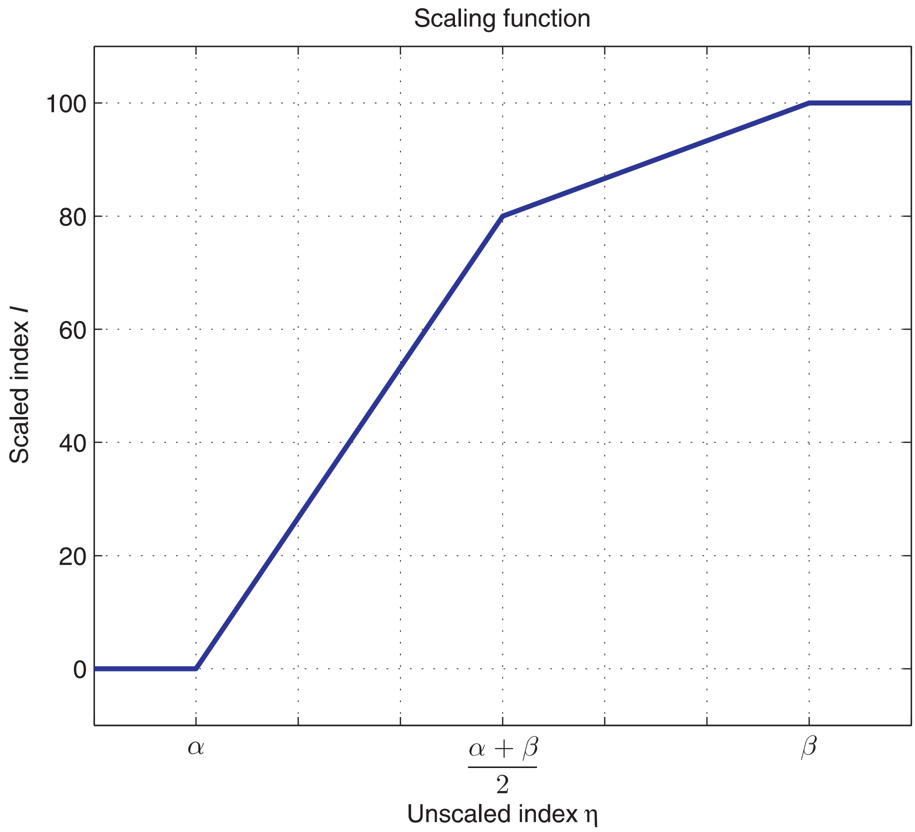


**Figure 5.4:** The piecewise linear scaling function in a case where larger measured values represent better performance.

## 5.3 High-level index hierarchy

It is possible to develop high level indices based on a combination of suitable low-level indices. Furthermore, the high-level indices themselves can be combined to create higher and higher levels of indices resulting in a hierarchical structure. The advantage of this approach is that on the highest level one could have only one index, the overall plant performance index. The overall index can be decomposed into the performance indices of different subsystems, lower level subsystems, and finally into the low-level indices.

The mathematical method for the combining is application dependent. Table 5.1 presents some suitable algorithms. When a performance index hierarchy is developed for an entire plant, it is most likely necessary to utilize several methods in order to obtain a performance monitoring system that shows clearly essential changes in performance. It must also be taken into account that an excessive amount of alarms from the performance monitoring system most likely leads to plant personnel ignoring them. Hence, only the most important changes in performance should be shown.

Using the arithmetic mean in aggregation is a straightforward initial guess. If a set of indices has a known impact on plant performance, the weighted mean could be used with weights chosen according to the relative importance of each lower-level index. Averaging, however, has the downside of hiding a single poor index if several others are on a good level. To find the weakest link in the plant, the minimum operator could be used in aggregation. It may, however, result in a pessimistic plant performance index with high variance. In order to combine the low variance of the mean and the emphasis on poor performance of the minimum, it is possible to use an aggregation function such as

$$f(\eta) = \frac{p_{1\%}(\eta) + p_{50\%}(\eta)}{2}, \tag{5.23}$$

where $\eta$ is an arbitrary performance measure and $p_{P\%}(\eta)$ is the $P^{th}$ percentile of $\eta$. Here $p_{50\%}(\eta)$ is the median of $\eta$, and could be replaced with the mean, while $p_{1\%}(\eta)$ could be replaced with the minimum. The replacements would result in an aggregation function which requires less computation time, but which is less robust than the one in (5.23). An alternative path would be to provide two indices on each of the higher levels: a mean-based index showing the average performance, and a minimum based index showing the weakest link.

The high-level indices contain the information of a number of lower-level indices. Hence, it is sufficient to monitor a small number of performance measures, and only if a high-level index shows deterioration, investigation of the corresponding low-level indices is necessary in order to find the root cause of poor performance. If the low-level indices are designed such that they only respond to a certain change in performance, isolating the root cause is straightforward.

The problem with relying on high level indices *only* is that if the control system

**Table 5.1:** Examples of methods for creating combined indices.

| Method | Definition |
|---|---|
| Minimum | $\min(x_1, x_2, \ldots, x_n)$ |
| Maximum | $\max(x_1, x_2, \ldots, x_n)$ |
| Arithmetic mean | $\frac{x_1+x_2+\ldots+x_n}{n}$ |
| Geometric mean | $\sqrt[n]{x_1 \cdot x_2 \cdot \ldots \cdot x_n}$ |
| Harmonic mean | $\frac{n}{\frac{1}{x_1}+\frac{1}{x_2}+\cdots+\frac{1}{x_n}}$ |
| Contraharmonic mean | $\frac{x_1^2+x_2^2+\ldots+x_n^2}{x_1+x_2+\ldots+x_n}$ |
| Truncated mean | A fixed amount of smallest and largest observations are removed from the data, the arithmetic mean of the remaining data points is computed |
| Quadratic mean | $\sqrt{\frac{x_1^2+x_2^2+\ldots+x_n^2}{n}}$ |
| Median | The observation in the middle of the sorted data |
| Midrange | $\frac{\min x+\max x}{2}$ |
| Trimean | $\frac{p_{25\%}(x)+2p_{50\%}(x)+p_{75\%}(x)}{4}$ |

$x_i$ arbitrary performance measure, $p_{P\%}(x)$ the $P$% percentile of $x$.

tries to keep the values of these indices as high as possible, incipient faults that the control system can compensate for will remain undetected until they clearly affect high level performance. In the meantime, in low level control loops excessive and costly control effort is used to keep the high level index at an acceptable level. (Hietanen *et al.*, 2005) This can be avoided by taking the low-level control effort into account when designing the performance indices.

## 5.4 Discussion

The selection of the scaling function is nontrivial. In initial work (Hölttä *et al.*, 2005; Hölttä, 2005), a piecewise linear scaling function was used (Section 5.2). Values above 100 and below 0 were truncated, but this was found impractical because of the lost information. This occurred especially when the scaling parameters were improperly adjusted, resulting in the saturation of an index to 100, and loss of performance information. The linear function also emphasized excessively the tails of the performance index distributions.

To overcome these shortcomings, continuously differentiable scaling functions were developed (Section 5.1). These scaling functions tend asymptotically to their extreme values. This preserves information of the extreme values of the original performance indices, the limiting factor being the accuracy of floating-point arithmetics.

There is an inherent trade-off between the number of parameters and the number of different shapes a scaling function can assume. In this work, a relatively small number of parameters was preferred in order to simplify the task of choosing parameters. Even with two parameters for each scaling function the total number of parameters grows excessively with a large number of performance indices. It seems, however, impossible to omit parameters completely, since the information on the different levels of performance needs to be included somehow in any performance assessment system.

The parameters of the piecewise linear scaling function are more intuitive than the parameters of the continuously differentiable scaling functions. However, with a different parametrization, also in the latter case it becomes possible to specify two unscaled index values that correspond to certain scaled index values (Equations (5.9) – (5.11)).

If the distribution of a low-level performance index is multimodal, although the index seems to be well-defined, there might be need for an operating point compensation. Varying load and operating conditions, and thus changing operating points of the plant, can be taken into account by binning the measurements and computing the indices individually for each bin. In practice, this means that the parameters of the scaling function should be determined individually for each distinct operating point.

To be able to compare performance at different operating points, it may be necessary to tune the scaling functions separately for each of them, further increasing the total number of parameters. If this is impractical, for example because of the large number of operating points, only low-level indices that are unaffected by the operating point can be utilized. Omitting some of the low-level performance indices to avoid tuning work may lessen the quality of the information given by the performance assessment system, as some of the performance related phenomena are not monitored by any of the performance indices.

# 6 Case: Simulation study

This chapter illustrates with the help of a simulated plant the usage of different low-level performance indices, and shows how an index hierarchy can be developed.

The plant in this example (see Figure 6.1) has two parallel subprocesses, which both can be modeled with the transfer function

$$G(s) = \frac{1}{s^2 + 2s + 1}. \tag{6.1}$$

During the normal operation of the plant, in addition to measurement noise with standard deviation 0.025, subsystem 1 is subject to stepwise load disturbances and subsystem 2 to an oscillating disturbance. The disturbance signals are shown in Figure 6.2. PID control (see Equation (2.2)) is used in both subsystems. This system is used to illustrate some of the performance indices reviewed in Chapter 2. To show how the different criteria react in different cases, the three sets of controller parameters in Table 6.1 are used.

**Table 6.1:** Controller parameters.

| Parameter | Slow tuning | Fast tuning | Oscillating tuning |
|---|---|---|---|
| $K$ | 0.50 | 1.00 | 1.70 |
| $T_I$ | 2.00 | 2.00 | 3.40 |
| $T_D$ | 1.00 | 1.00 | 0.59 |

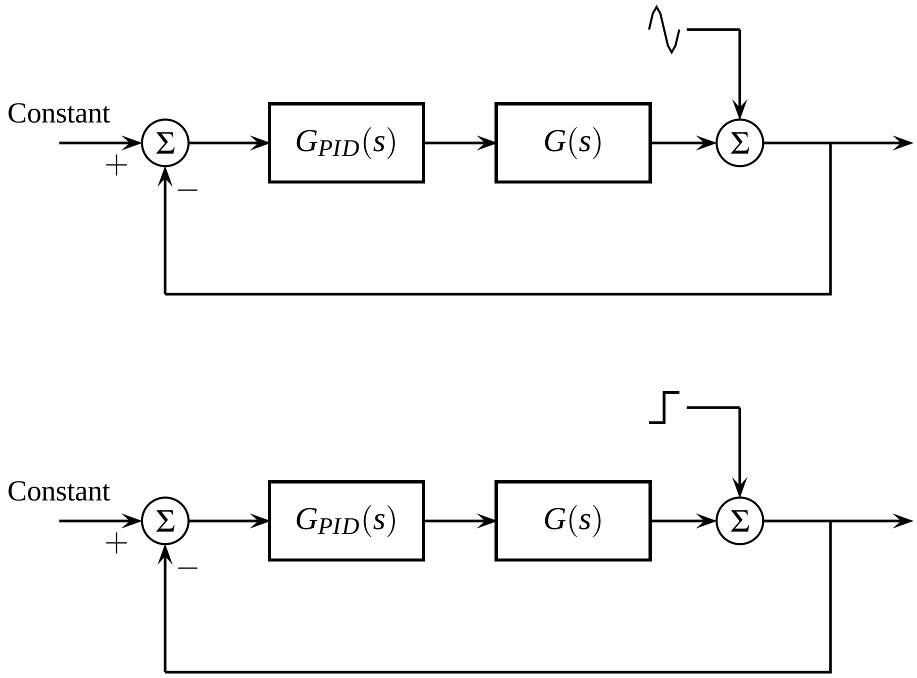


**Figure 6.1:** The structure of the simulated plant used in the example. The plant has two production lines that are subject to different load disturbances.

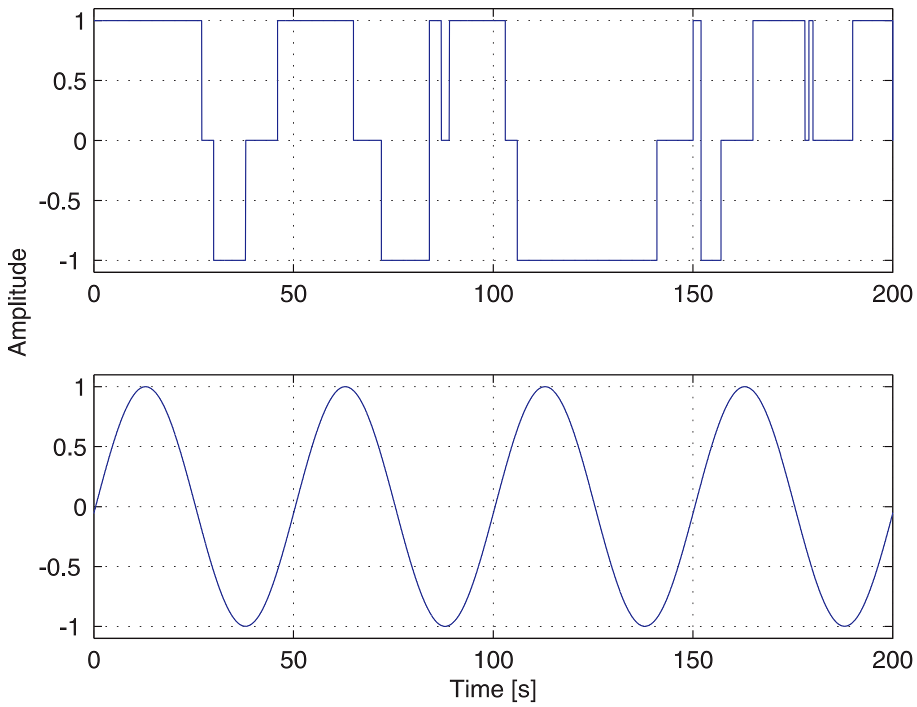


**Figure 6.2:** The load disturbance signals affecting subsystem 1 (top) and subsystem 2 (bottom). The same disturbance signal is repeated for each set of controller parameters.

## 6.1 Step response performance assessment

The step responses of the subsystem are in Figure 6.3 and the corresponding values of the step response criteria in Table 6.2. These values were computed using a simulation time of 20 seconds.

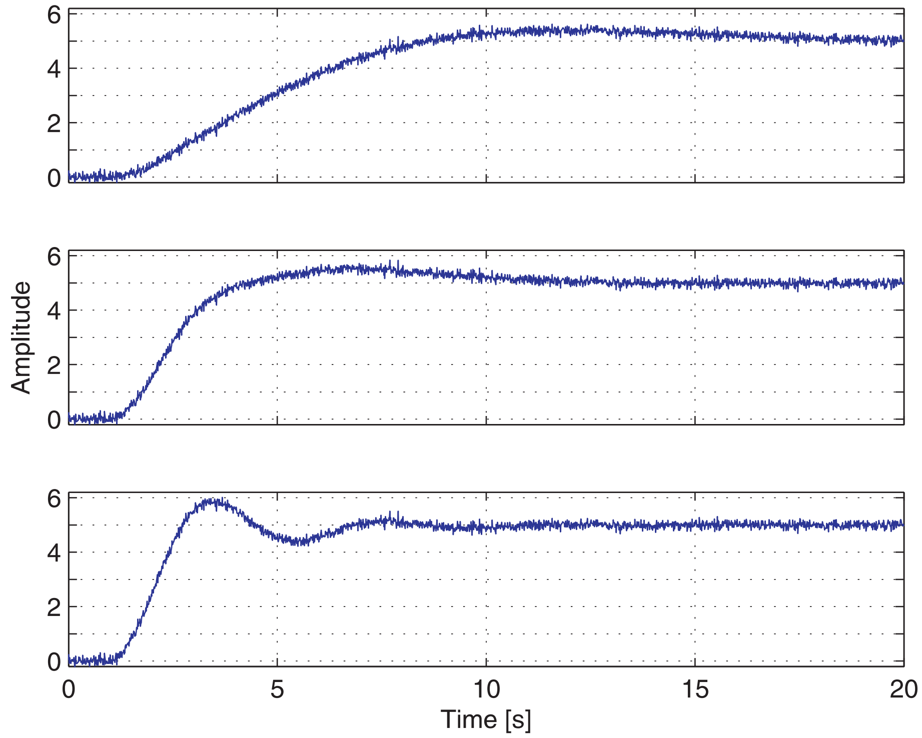


**Figure 6.3:** The step responses of the system with different controller parameters, reference $y_r = 5$. Top: slow tuning, middle: fast tuning, bottom: oscillating tuning.

## 6.2 Online performance assessment

### 6.2.1 Low-level indices

To be able to monitor the performance of the process online, the permanent error index (PE) and the sluggish control index (SL) (see Section 2.4) are computed online. The maximum acceptable error, $e_{lim}$, for the PE index is set to half the standard deviation of the respective error signal. For each index, the forgetting factor is 0.999.

**Table 6.2:** Values of step response performance criteria.

| Criterion | Slow tuning | Fast tuning | Oscillating tuning |
|---|---|---|---|
| $\eta_{ISE}$ | 8550 | 5160 | 4477 |
| $\eta_{ITSE}$ | 17950 | 6294 | 4612 |
| $\eta_{IAE}$ | 2502 | 1519 | 1295 |
| $\eta_{ITAE}$ | 9442 | 4429 | 3385 |
| $\eta_w$ | 155814 | 463914 | 469851 |
| Dead time [s] | 1.0 | 1.0 | 1.0 |
| Rise time [s] | 5.0 | 1.9 | 1.2 |
| Overshoot [%] | 12.3 | 16.7 | 20.2 |
| Settling time [s] | 18.4 | 19.7 | 18.2 |

See Chapter 2 for the definitions of the performance criteria. For $\eta_w$, $w_1 = w_2 = 1$.

The process was simulated for 600 seconds of simulation time, with the controller parameters changed after 200 and 400 seconds. The time series plots of both subsystems' control errors are in Figure 6.4 and the corresponfing performance indices are in Figure 6.5. The values of both indices are by definition between $-1$ and 1. The value of the PE index is poor when it is close to $\pm 1$, whereas the value of the SL index is poor when it is close to 1.

### 6.2.2 Normalized performance index hierarchy

As the first step in creating an index hierarchy for the system, the indices defined above are scaled to the open interval $0 \ldots 100$. The absolute values of the PE indices are evaluated. Then all PE and SL indices are scaled using the decreasing scaling function (Equation (5.1)) such that the unscaled index values 0.1 and 0.8 correspond to the scaled index values 90 and 30, respectively ($k \approx 109$ and $\eta_{50} \approx 0.605$). The scaled indices are in Figure 6.6. After the scaling, the index value 100 indicates good performance in each case.

When the indices form a tree-type structure, they are naturally visualized as such

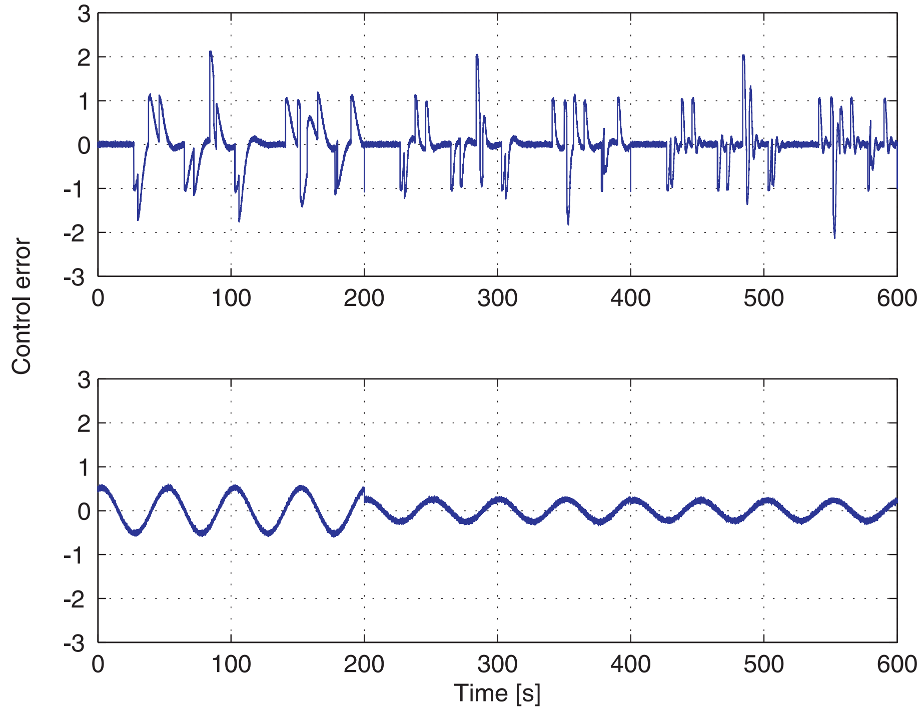


**Figure 6.4:** Control errors of subsystem 1 (top) and subsystem 2 (bottom). Controller parameters change after 200 and 400 seconds from slow to fast and finally to oscillating.

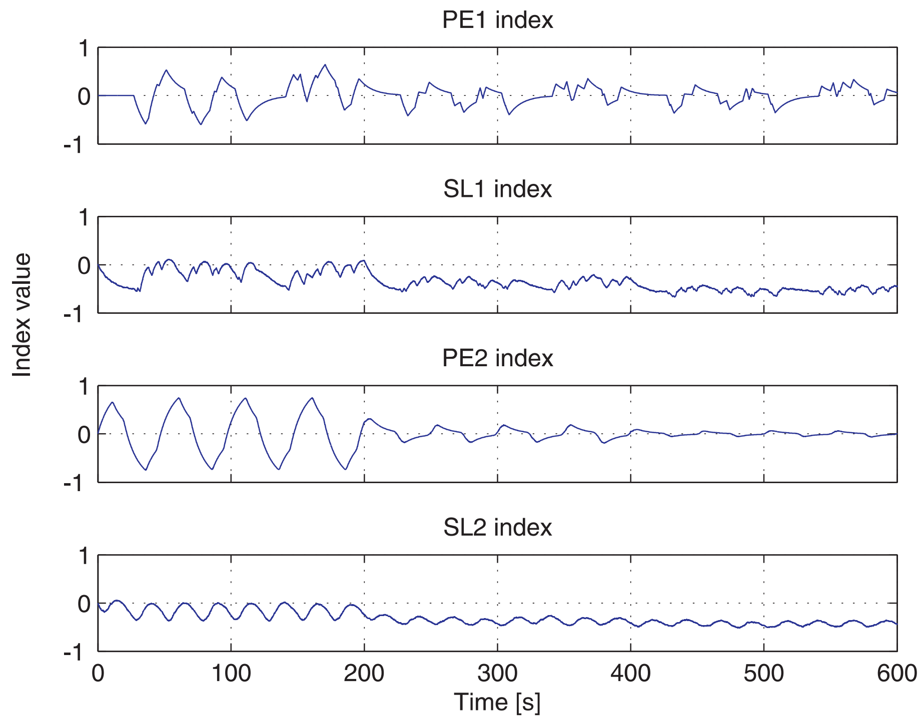


**Figure 6.5:** Values of the PE (see Equation (2.43)) and SL (see Equation (2.49)) performance indices. The numbers in the index names indicate the subsystem. Controller parameters change after 200 and 400 seconds from slow to fast and finally to oscillating.

(Shah *et al.*, 2005*a*; Shah *et al.*, 2005*b*). Figure 6.7 shows an index hierarchy for the simulated system. The PE and SL indices of a subsystem are combined to

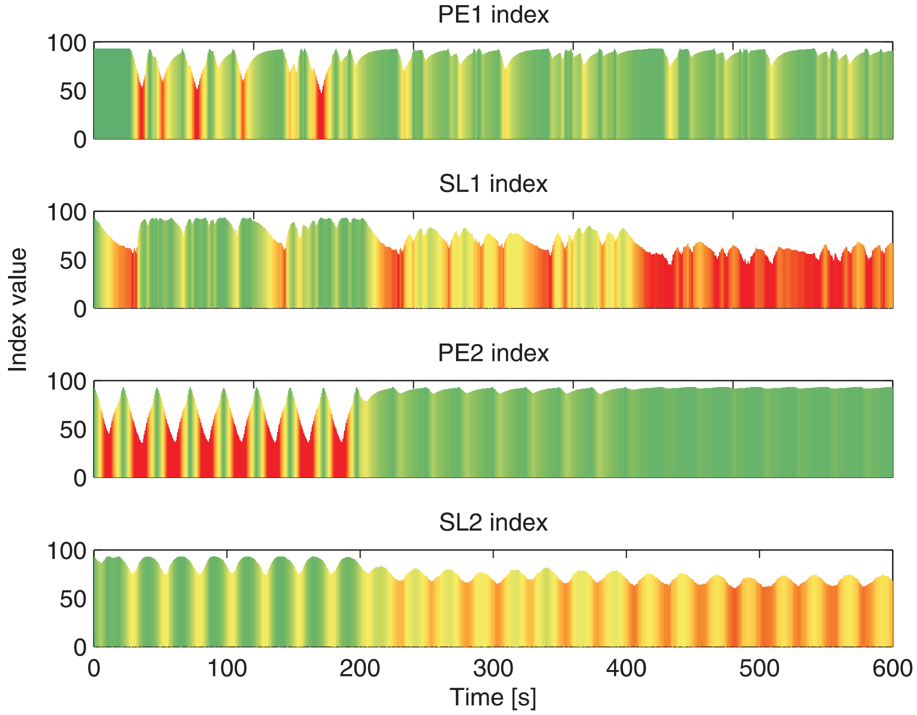


**Figure 6.6:** Values of the scaled PE and SL performance indices. The numbers in the index names indicate the subsystem. Controller parameters change after 200 and 400 seconds from slow to fast and finally to oscillating.

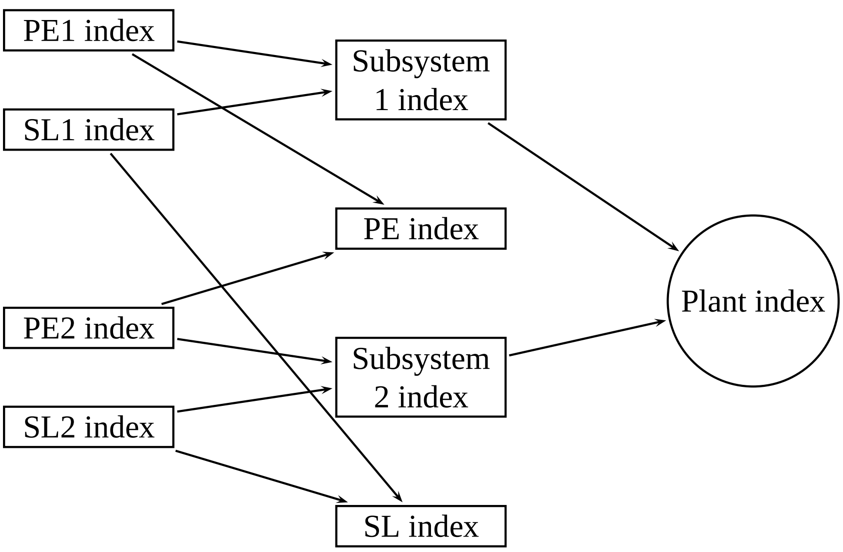


**Figure 6.7:** An index hierarchy for the simulated plant. The two subsystems have their own indices, which are aggregated into a overall plant index. In addition, there are indices describing the general levels of set point error as well as sluggish control.

obtain the performance index for the subsystem. The subsystem indices are then aggregated into an overall plant performance index. On the other hand, the PE

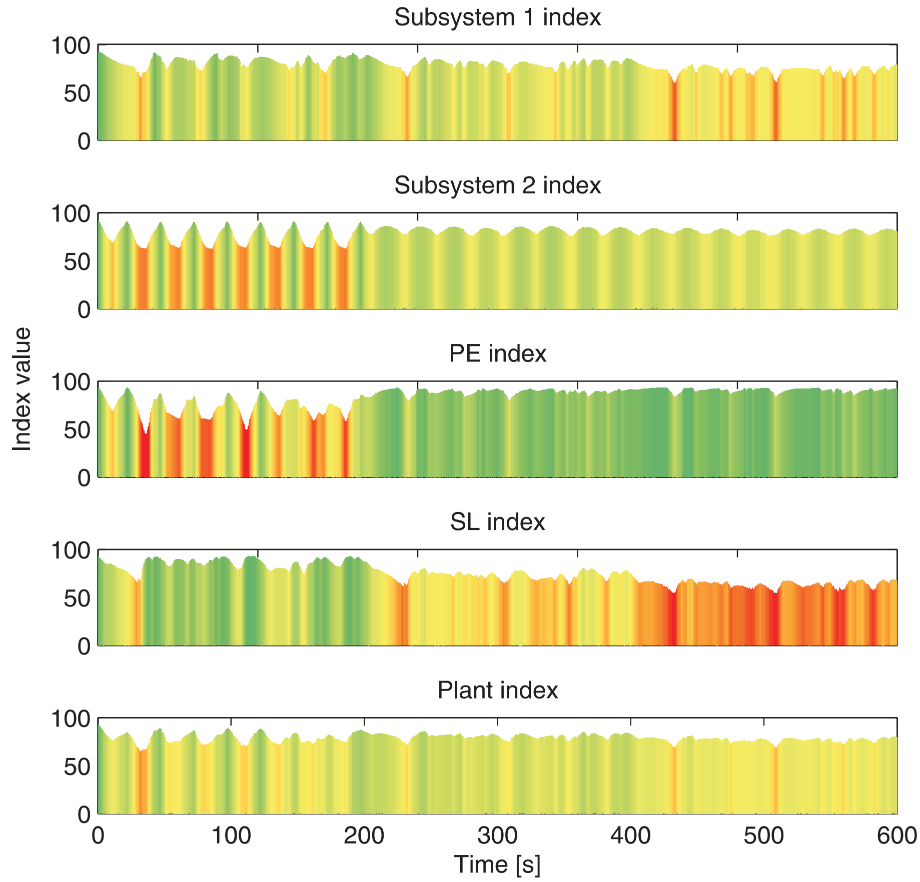


**Figure 6.8:** Values of the high-level performance indices. Controller parameters change after 200 and 400 seconds from slow to fast and finally to oscillating.

and SL indices from different subsystems are grouped to corresponding plant-wide indices. In each case the arithmetic mean is used as the aggregation function. The resulting index time series are in Figure 6.8.

## 6.3 Discussion

This example shows how different performance indices can be used when assessing the performance of a plant in general, or when selecting the parameters of a controller. This example showed how three sets of controller parameters produce a qualitatively different step response. The values of the step response criteria in Table 6.2 change accordingly. The selection of the best controller is application dependent, since no controller is able to minimize all criteria, for example, a decrease in rise time is accompanied with an increase in overshoot.

To be able to interpret the performance index values in Figure 6.5, one must know the meaning of the values, which happens to be different in the case of the two indices. Once the indices have been scaled (Figure 6.6), this is no longer required. Based on the scaled indices, it is possible to create new indices that summarize performance with respect to a subsystem, or a certain feature.

By looking at the levels of the index values in Figures 6.6 and 6.8, it is possible to distinguish the time periods where different controller parameters have been in use, whereas using control error (Figure 6.4) alone it is difficult to see the difference between fast and oscillating tuning. In both subsystems, the slow tuning produces low values in the case of the PE index, and high values for the SL index. Judging by the index values, the slow tuning is most suitable for subsystem 1, and the fast tuning for subsystem 2, since they produce the best overall index level for the subsystems. If performance was still regarded to be inadequate, it would be possible to evaluate the performance indices for additional controller parameter sets and control structures, and to compare the results.

# 7

# Case: Evaluation of the technical performance of forest harvesters

This chapter introduces the reader to the basic operation of a cut-to-length forest harvester. Then it shows how the performance index framework was applied to evaluate the technical performance of a cut-to-length forest harvester.

## 7.1 Mechanised timber harvesting

Forest machines, as well as other agricultural and construction equipment, are examples of machines with complex electro-hydraulic systems controlled by embedded microcontrollers, and with large amounts of signals and data distributed via a digital network. The operating conditions of these machines are typically demanding: environmental and load conditions can change significantly during one work shift. In spite of the harsh operating conditions, the machines are expected to perform faultlessly and efficiently between service intervals. To maximize uptime and to guarantee efficient operation, condition monitoring and performance assessment are needed to be able to detect and to correct proactively impending faults before severe machine failures occur.

Two main working methods are used in mechanized timber harvesting: the full-tree and cut-to-length methods. Various types of equipment and machines are used

**Figure 7.1:** A cut-to-length forest harvester which is used for felling and delimbing trees and cutting them into logs of predetermined length.

depending on how the wood is utilized and processed at the saw or at the pulp mill. In the full-tree method the stems are transported intact from the forest, whereas in the cut-to-length method the stems are cut into logs of predetermined dimensions. Full-tree harvesting machines are more conventional having one or two processing functions, whereas cut-to-length harvesting machines are technologically more sophisticated and have more versatile processing operations.

In the cut-to-length method trees are felled, delimbed and bucked (i.e. cut to logs) with a forest harvester (Figure 7.1). The harvesters are computer controlled and are equipped with measuring devices that measure the length and diameter of the tree stem. An optimization system assists in bucking of the log lengths in order to maximize the value of the stem. Once the stems are processed on the logging site, a forwarder carries the logs to the roadside for further transportation (Figure 7.2).

A cut-to-length forest harvester can be divided into four main parts: engine and power transmission, cabin and controls, boom and harvester head. The diesel engine rotates the supply pumps for work hydraulics and for hydrostatic transmission. The former supplies hydraulic power to the boom, to the harvester head and to all auxiliary functions of the machine. Hydrostatic transmission consists of a variable displacement pump, a variable displacement hydraulic motor and mechanical

**Figure 7.2:** A forwarder which is used for carrying the logs to the roadside.

transmission to the wheels.

The cabin is equipped with the controls for operating the machine functions and with a computer display module, which gives the operator information on the harvesting process and the operating state of the harvester.

The different parts of the harvester are interconnected via a controller area network (CAN) bus. The bus enables two-way digital communication between the harvester head, the crane and other modules.

The most complex and important part of the harvester is the harvester head. The main functions of the harvester head are sawing, feeding, delimbing of branches, as well as measuring log length and diameter profile. The performance and functionality of the harvester head determine the overall timber harvesting efficiency of the machine, and the quality of the harvested timber.

Trees are felled and stems are cut to logs with a hydraulically actuated chain saw. Once sawing is complete, the stem of the tree is fed to the next cutting point with feeding rollers rotated by hydraulic motors. The grip of the feeding is ensured by pressing the feeding rollers against the stem with a hydraulic cylinder. The stem is grasped into the harvester head with two pairs of delimbing knives, which are closed circumferentially around the tree trunk. Tree branches are cut by means of the feeding force when the stem is fed between the delimbing knives. The typical feeding speed of the system from 3 m/s to over 5 m/s gives an idea of the performance and the processing pace of the harvester.

For many fault types in the forest harvester it is typical that the component progresses through a series of degradation states before a permanent failure occurs. An internal leakage in a hydraulic cylinder is an example of such a fault. Prior to the eventual failure state of the component, the impending fault may cause occasionally impaired performance in a certain machine function. The objective of this application example was to create methods to assess the technical performance of a forest harvester and to find the machine functions that are responsible for poor performance. The root cause can be also control system parameters that are not suitable for the current operating conditions.

The recent trend in off-highway machines is that more and more of them have been equipped with onboard computers. Embedded control systems and microcontrollers have been in use already for some time, but the processors that run embedded code are often of modest performance. However, onboard vehicle computers with modern processors and ample memory and hard drive space possess a computational and storage capacity that permit the use of advanced algorithms in various fields of application other than mere control of machine functions, such as performance assessment and logging of performance data.

## 7.2 Special aspects of performance evaluation in forest harvesting

In this application, the objective was to monitor the technical performance of a forest harvester. By inspecting harvester logbooks, it can be seen that the productivity of a machine measured in units of volume processed in a fixed time varies greatly.

It is assumed that most of this variation is caused by external factors such as:

- environmental issues such as temperature, rain, and snow,
- processing different tree species,
- machine parameters are changed,
- the operator changes,
- the operator changes working practices,
- the stand changes.

The objective when setting up a system for assessing the technical performance was to compensate the effect of the above-mentioned factors, and to extract the changes that are due purely to changes in the technical condition of the machine.

Additionally, forest harvesting is not a continuous production process in the sense that subsequent trees may be very different with respect to size, to location of branches, and to other factors affecting performance. Hence, productivity for trees processed one after another may differ, while it is probable that the technical performance of the machine has not changed significantly.

## 7.3 Implementation of performance assessment system

### 7.3.1 Technical level

The different control modules of the harvester produce raw data during operation, and distribute this data via the CAN bus to other modules on the machine. In this implementation, no changes were made to the technical level, as processing the raw data gave sufficient performance information.

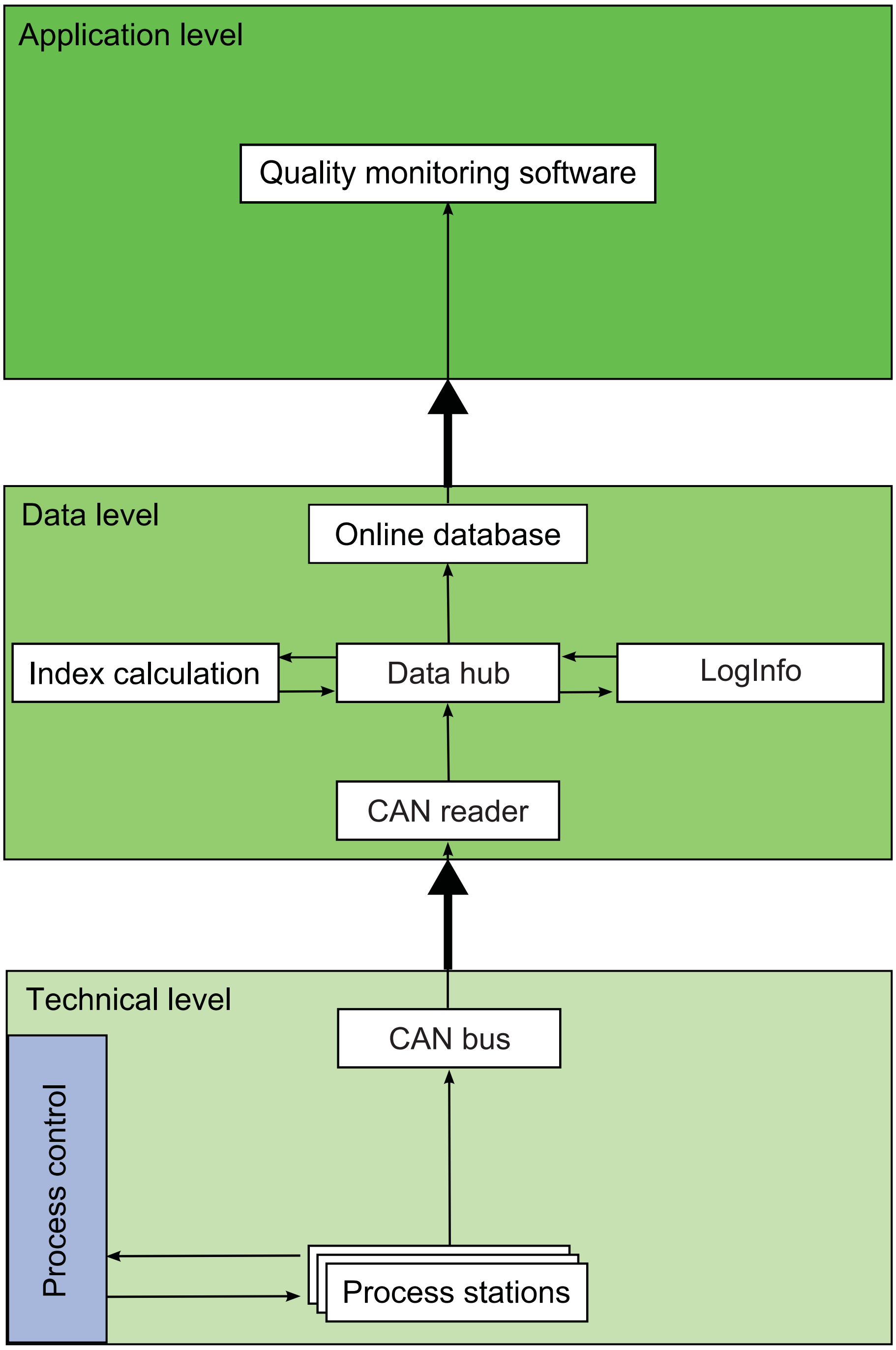


**Figure 7.3:** The data collection and processing infrastructure in the forest harvester.

### 7.3.2 Data level

Index computation was implemented in the onboard computer of the harvester. The computer is an industrial PC running the Microsoft Windows operating system. The harvester has a component-based information management system. The CAN reader software component picks relevant messages from the bus, and the data are distributed to different user components via a data hub. Based on the data from the CAN bus, a component (LogInfo) creates processing data for each stem and each log. The processing data has about 50 variables for each stem and more than 50 variables for each log of the stem. The data are stored in the harvester using the extensible markup language (XML) format (see Table 7.1).

The index calculation component is responsible for computing performance data using production data. The index calculation sequence is depicted in Figure 7.4. Outlier removal was based on threshold values derived from physical constraints and experience. Measured values that exceed the upper bound or are below the lower bound are regarded as outliers. The thresholds were determined individually for each measurement. Outliers were removed from the data and were not used in index computation in any manner.

Compensation is done by binning the measurements into discrete classes corresponding to different operating conditions. Before the number of classes and the boundary values were selected, the probability of each potential class was considered so that there would be a sufficient amount of data in each bin. Variable-by-variable and index-by-index consideration was needed to determine the need of compensation because some variables are not affected by changes in operating conditions.

The indices are computed separately for each bin using the piecewise linear scaling function presented in Section 5.2, and the combined index value for all measurement bins is computed as the weighted arithmetic mean over all bins. The selection of weights is based on the importance of the underlying measurements to perfor-

**Table 7.1:** Example of the XML file created by LogInfo.


```
<Stem TIME="2007:11:01:13:05:01:431" LogInfo.Version="6.10.3">
  <FellingTime u="s">0.648</FellingTime>
  <FellingDiam u="m">0.114</FellingDiam>
  <CatchingTime u="s" WARNING="TRUE">26.507</CatchingTime>
  .
  .
  .
  <MaxDiam u="m">0.750</MaxDiam>
  <MinDiam u="m">0.082</MinDiam>
  <Log TIME="2007:11:01:13:05:15:662">
    <PartlyManualAcceleration>FALSE</PartlyManualAcceleration>
    <PartlyManualFeed>TRUE</PartlyManualFeed>
    <StartStuck>FALSE</StartStuck>
    .
    .
    .
    <ForcedDKTime u="s">0.000</ForcedDKTime>
  </Log>
  <Log TIME="2007:11:01:13:05:25:412">
    <PartlyManualAcceleration>FALSE</PartlyManualAcceleration>
    <PartlyManualFeed>TRUE</PartlyManualFeed>
    <StartStuck>FALSE</StartStuck>
    .
    .
    .
    <ForcedDKTime u="s">0.000</ForcedDKTime>
  </Log>
  .
  .
  .
</Stem>
```


mance.

### 7.3.3 Application level

A browser-based used interface (Figure 7.5) allows access to the performance index data. The user sees on the front page the most essential data, and based on this overview, can choose to look at the performance of individual subsystems. Com-

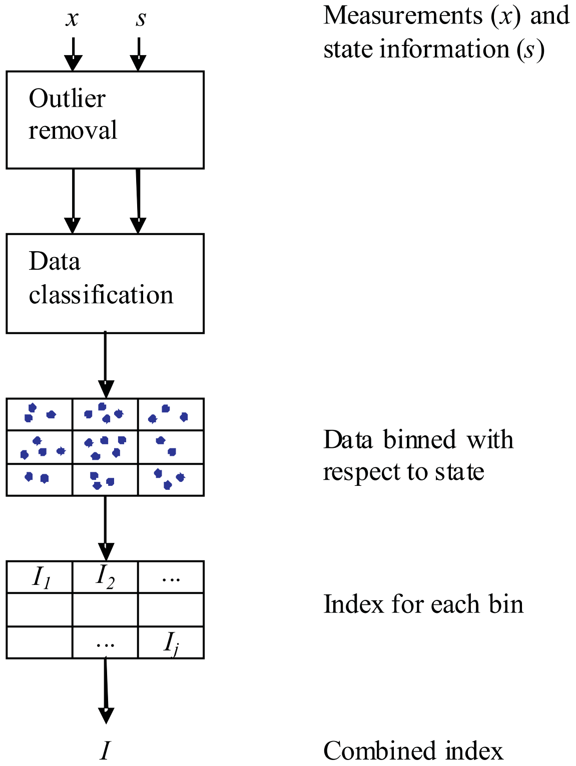


**Figure 7.4:** Schematic representation of the computation of normalized indices.

parisons between different time periods are possible, if there is reason to suspect that a change in performance has occurred.

## 7.4 Usage of performance assessment

Figures 7.6 and 7.7 show an example of some of the indices related to the forest harvester. Two cases are presented in order to enable comparison: during the data gathering period harvester A felled about 16 000 trees, whereas harvester B felled 11 500 trees. Each one of indices 1-6 represents a different subsystem or function in the harvester.

There are several interesting features in the figures. First of all, most indices are close to 90 for most of the time, thus indicating good overall performance. The variance of the indices differs for different indices. There are also dissimilarities between the two harvesters: index 1 for harvester B is much smoother than for harvester A.

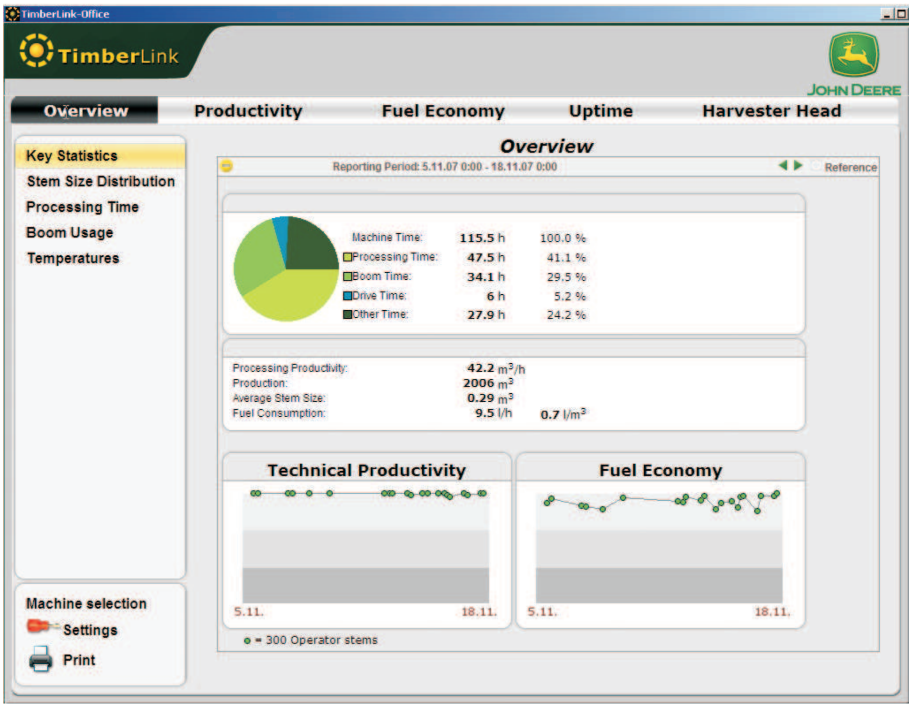


**Figure 7.5:** An example of the TimberLink user interface. In the bottom of the screen time series index data for technical productivity and fuel economy is shown.

In some cases, like for index 5 of harvester A in the beginning of the data gathering period, the value of the index starts to decrease steadily and finally collapses to a low level. After this the index returns to a good level, indicating that the cause of low performance in the particular subsystem has been identified and corrected. The indices describing different subsystems in one machine should not correlate with each other if the subsystems are physically and functionally distinct. This is indeed the case in the above-mentioned example where index 5 of harvester A decreases while the other indices remain unchanged.

Measurement data were gathered over a relatively long period of time from both harvesters, which means that the operating conditions have changed several times. However, the indices show only occasional, but not regular and repeated changes, indicating that compensation of disturbances is working properly.

When the indices have been designed such that they do not correlate with each other, they can be used indirectly for condition monitoring. The performance as measured by the indices can be assumed to correlate with the condition of the sensors and actuators in the respective subsystem. In a complex system with a

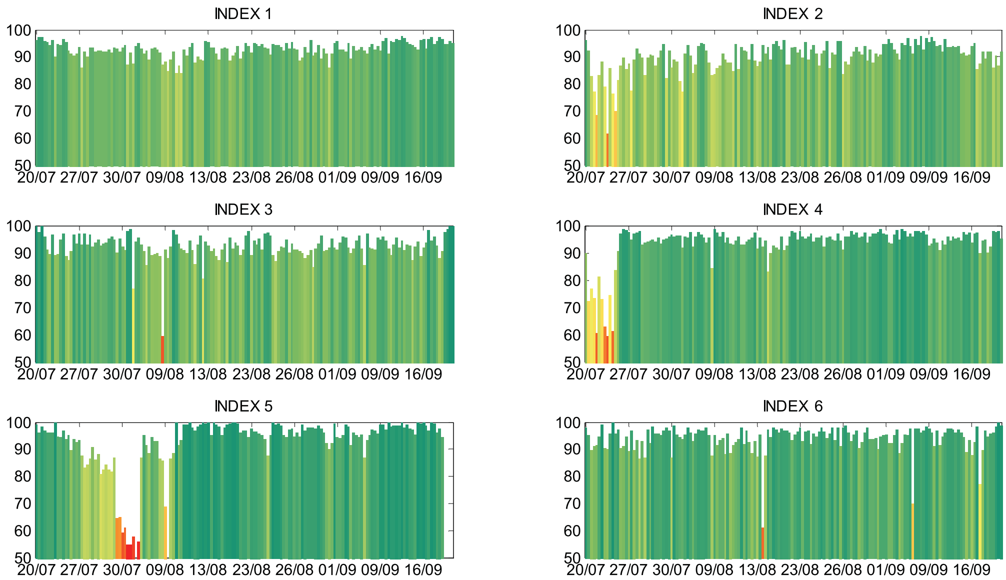


**Figure 7.6:** Indices for harvester A as a function of time.

limited number of measurements it is not reasonable to expect that a fault can be pinpointed exactly in all cases. However, when the indices are at the disposition of the maintenance personnel, the cause of poor performance can be isolated to a particular subsystem before anything else is done. This reduces significantly the time and cost of maintenance.

Usually pinpointing the faulty components requires additional measuring equipment or special test sequences, so it must be done offline. When performance assessment is carried out during normal working cycle using the indices, the need of maintenance can be evaluated real-time and there is no need of periodically launching unnecessary test sequences.

Many existing condition monitoring methods require comprehensive teaching data that are labeled with fault information. Acquisition of such data from a complex industrial process can be nearly impossible. When the indices are used, labeled data are not needed, because the indices are related to performance in general, and not to certain faults. It is left to the responsibility of the maintenance personnel to locate the precise fault from the subsystem the indices deem to have low performance.

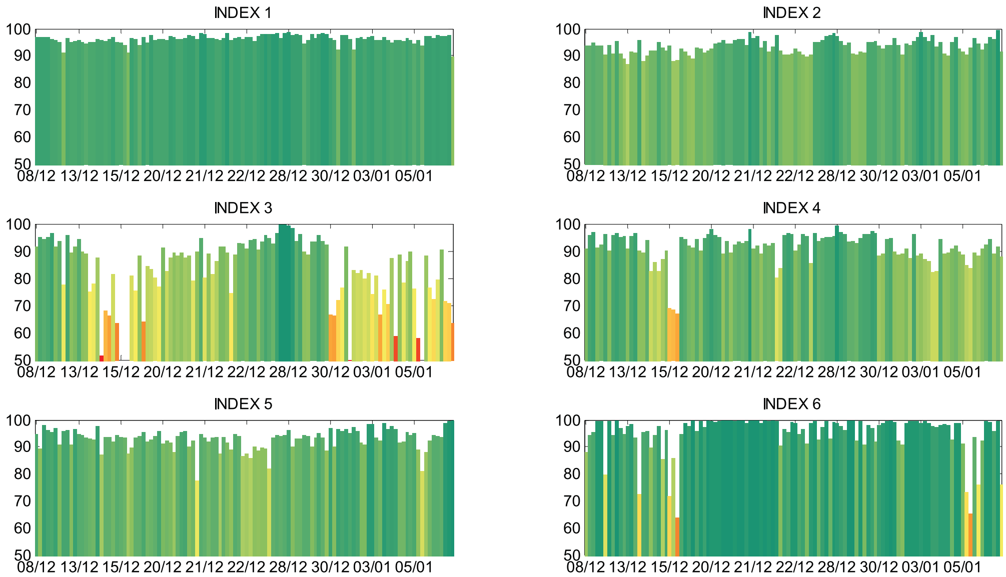


**Figure 7.7:** Indices for harvester B as a function of time.

## 7.5 Discussion

The performance index framework that was developed for assessing the technical performance of forest harvesters was implemented to the control system of the harvester, and it is possible to purchase it with a harvester. According to application experts, it has proven to be a valuable tool in performance evaluation and in finding performance bottlenecks. With the indices it has become possible for the first time to assess the performance of certain functions of a forest harvester and to compare different harvesters.

Currently, there are index data available from several hundreds of harvesters, and these data have been studied in detail elsewhere to find new uses for the performance information (Tikkanen *et al.*, 2008; Hyvämäki, 2009). Work with performance evaluation has continued with the forwarder, and methods for operator skill assessment have been developed (Tervo *et al.*, 2009; Tervo *et al.*, 2008).

In the present application, adding new sensors solely for evaluating performance is not feasible. Instead, the indices are computed using the data the control modules share via the CAN bus of the machine. Metrics for machine performance follow-up are derived from these multidimensional data, which have strong nonlinear correlations between some of the measurement variables.

The piecewise linear index normalization scheme was used in this application. In spite of the shortcomings of this method discussed in Chapter 5, the normalization method was successfully applied. However, this work resulted in the development of a more general approach.

Onboard computers on different types of off-highway working machines possess a significant computational capacity that can be harnessed for applications such as performance assessment. This enables the implementation of the performance assessment framework described in this chapter to a large class of mobile working machines.

# 8 Case: Evaluation of paper quality at the paper mill

This chapter presents the parts of the paper manufacturing process and then shows how the performance index framework was applied to evaluate paper quality.

## 8.1 Paper manufacturing

The process for industrial papermaking is the result of a long evolution. The principal raw material in the process is wood, and the purpose of the process is to transform logs into sheets of paper with different physical and optical properties.

Paper products can be divided into two classes based on their grammage: paper (basis weight 6–150 g/m$^2$) and paperboard (125–600 g/m$^2$). Applications for paper include printing and writing, packaging, and hygiene. Paperboards are used for cartonboards, container boards, and graphical boards. (VTT Technical Research Centre of Finland and Prowledge Oy, 2009) The manufacturing process for all these products is similar.

The paper manufacturing process consists of different phases: First, the wood is harvested (see Chapter 7) and transported to the mill. The wood is processed into pulp, where the cellulose fibers have been separated from each other. In the paper machine, the fibers rejoin and form a continuous web of paper as water is removed. The paper produced in this manner may be processed further by coating and calandering in order to improve quality.

Pulp can be produced either in the chemical or in the mechanical pulping process. In chemical pulping, the structure of the lignin connecting the cellulose fibers is broken chemically, allowing the fibers to separate. In mechanical pulping wood is fiberized using mechanical action together with increased temperature and pressure. The properties of the pulp produced in the two processes are different. Chemical pulp has longer fibers because the connecting substance is washed away rather than removed mechanically. As an result, paper produced using chemical pulp is stronger. However, the yield of the pulping process is inferior to the mechanical process in which the lignin is not removed from the pulp. Because of the presence of lignin, paper produced using mechanical pulp is less resistant to the effect of time.

The pulp fed to the paper machine may contain a mixture of different pulp types as well as broke, which is rejected paper originating from the paper manufacturing process, and pulped recycled paper. Additives may be mixed to the pulp to improve the properties of the paper.

The headbox of a paper machine distributes the pulp uniformly on the wire of the paper machine to produce the paper web. In the headbox, the water content of the pulp is more than 99 %. While the web is on the wire, water is removed by means of gravity and suction. The web is transferred from the wire to the press section, where further water is removed using mechanical force. The web, supported with a felt, passes between cylinders, and water is absorbed by the felt. The final drying of paper takes place in the dryer section. Water is removed by means of steam-heated cyliders, resulting in a water content in the order of 5 %. Finally, the paper is passed through the machine calender, which controls the thickness of the paper and improves the finish of the surface of the paper.

When producing coated paper for e.g. magazines, the paper produced in the paper machine can be coated in order to improve the appearance and printability of the

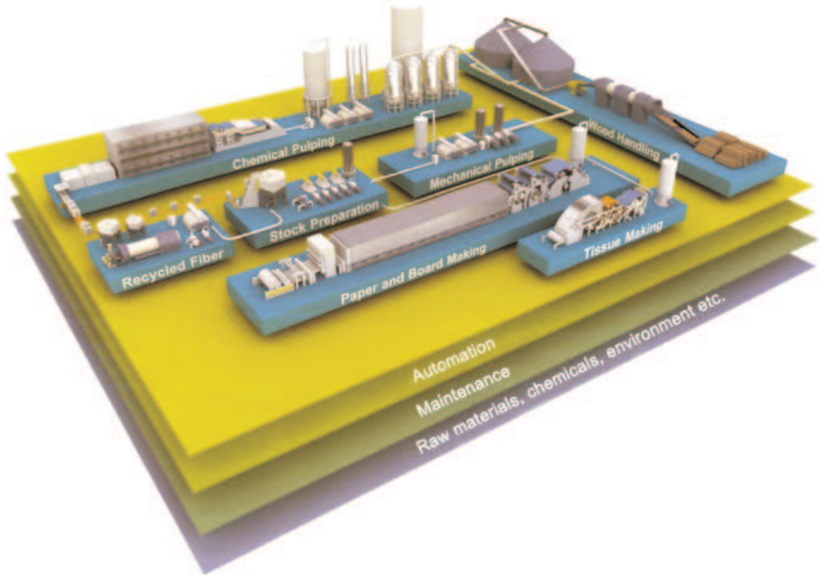


**Figure 8.1:** The phases of paper production. (Image courtesy of Metso Corp.)

paper. During coating a pigment (e.g. kaolin, talc, or carbonate) and a binding agent (e.g. starch or latex) are applied to one or both sides of the paper. An excess of the coating substance is spread on the paper, the surplus is removed, and the coating is dried. Depending on the intended use of the product, up to three layers of coating can be applied.

Finally, the paper can be passed through a calender, which finishes the appearance and other properties of the paper. Calandering affects web dimensions, smoothness, color, gloss, strength, and stiffness.

Before paper can be delivered to the client, machine reels must be cut to smaller customer reels which are then packaged in order to be resistant to damage during transportation. If done correctly, these operations have no effect on the quality of the paper.

## 8.2 Special aspects of quality assessment in paper manufacturing

Several variables affecting the quality of the paper are measured online from the web, including moisture, basis weight, caliper, opacity, and ash content. Other variables, including tensile, tear, and bonding strengths as well as stiffness, are impossible to measure online, since the measurement may require breaking the paper. These measurements are done in the laboratory.

Since it is impossible to distribute the pulp uniformly on the web, the above-mentioned quality variables vary in the direction perpendicular to the movement of the wire (cross direction), and, for instance, process variations in pulp mixing cause variations in the direction of the movement of the wire (machine direction). Figure 8.2 shows a typical cross-section of the moisture of the paper web. Features impairing paper quality are visible: Firstly, the value of the variable is smaller on the edges of the web than in the middle, making the shape of the cross-section suboptimal. Secondly, if several successive cross-sections are studied, it is seen that the value at certain points remains smaller or larger than the surrounding values. This type of feature is known as a streak, and it shows in the figure as distinct peaks.

Quality control is commonly based on laboratory measurements. These measurements become available only after a delay, which might be as long as an hour. The sample that is measured in the laboratory is a narrow strip of paper taken from the end of the machine reel. The laboratory measurement is used to represent the value of a variable for the entire reel, although it is probable that there are considerable variations within the reel in both CD and MD.

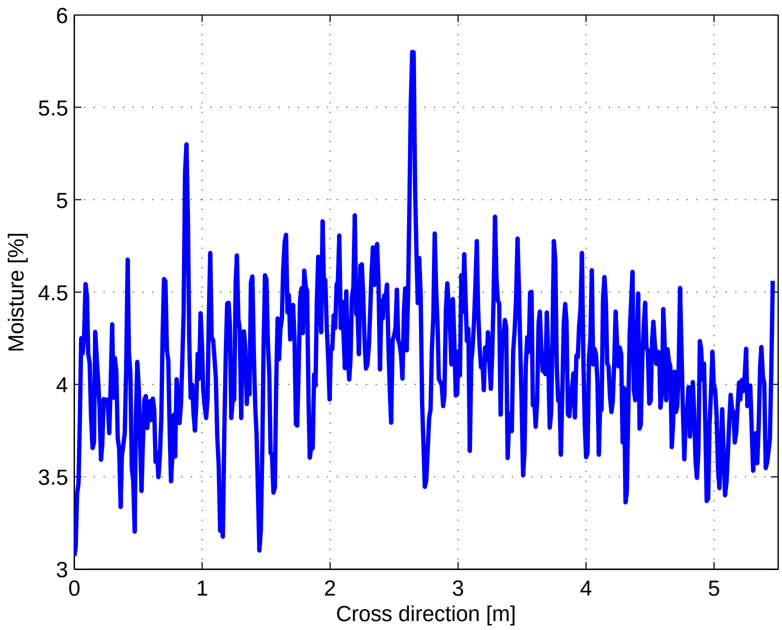


**Figure 8.2:** A typical cross-section of the moisture of the paper web in the cross direction.

## 8.3 Implementation of quality assessment

### 8.3.1 Technical level

The scanner data stored in the automation system was averaged both in CD and in MD, and existed in unfiltered form only in the scanners. Therefore, direct access to the scanners was necessary. A connection to the automation system was also needed to be able to gather supporting process measurements. To enable easy access to data originating from different devices, OPC was chosen to be the technology for data acquisition. Further advantages of OPC included the availability of the OPC server-side software from the control system provider, and of a suitable OPC client able to store the data into a database for future access.

OPC is an open standard for different levels of connectivity between industrial automation and supporting systems (OPC Foundation, 2009). Originally the standard was called OLE for Process Control (OPC) (Pattle and Ramisch, 1997; Chisholm, 1998), but currently only the abbreviation is in use. Development of the first OPC standard, the current Data Access Specification, started in 1995. It was based on

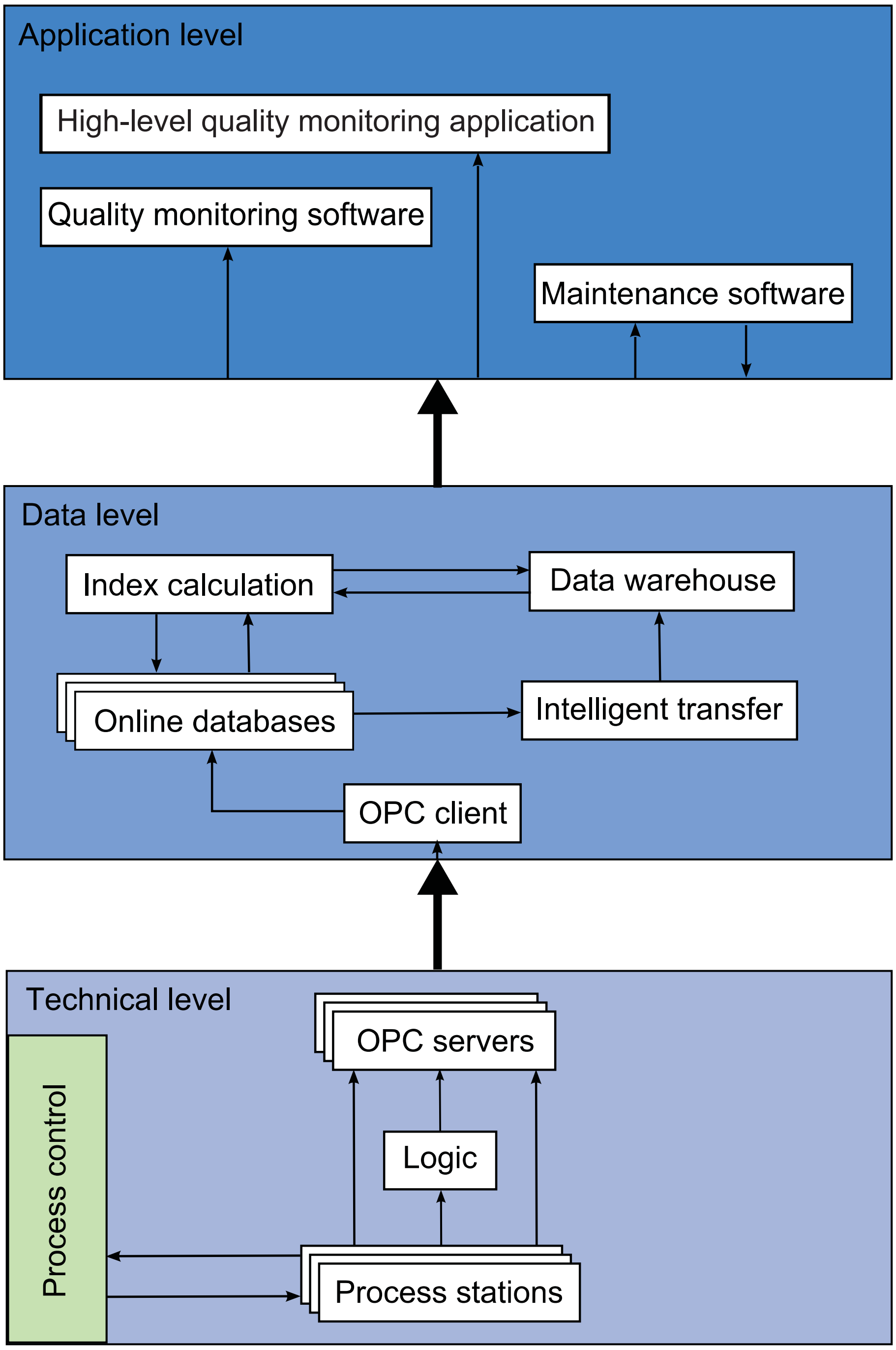


**Figure 8.3:** The data collection infrastructure in the paper mill. Adapted from (Mattsson, 2009).

the COM/distributed COM (DCOM) model and aimed at the standardization of the acquisition of process data. (Pattle and Ramisch, 1997; OPC Foundation, 2009) The standard defined methods and objects to be used in communication between software applications irrespective of the environment the applications were run (Pattle and Ramisch, 1997). Since the beginning, standards have been added, for example, for communicating alarms and events, batch process data, historical data as well as commands. Recently, the OPC Unified Architecture specifications have provided standards that are not based on the COM model and thus are platform independent (OPC Foundation, 2009).

### 8.3.2 Data level

On the data level, an OPC client receives the relevant data from the OPC servers, and stores them in an SQL database. The measured variables include moisture, basis weight, caliper, opacity, and ash content, all affecting the quality of the paper. There exists a separate online database for each production line. The data in the databases are organized corresponding to the physical manufacturing process: a new row is created in the top-level table (see Table 8.1) of the database once a machine reel enters the next production phase (paper machine, coating machine, and calander). Due to the large data rate from the scanners, profile data are compressed in the databases. The compression is lossless so that the original measurements can be restored without loss of accuracy.

An index calculation software component polls the online databases at regular intervals, and once new measurements are available, it computes a set of quality indices and stores them into the online databases. For the long-term storage of the data, a data warehouse is used, containing process and quality data from all production lines. The index calculation software can also recompute indices in the data warehouse if, for example, a change in index parameters is needed.

An intelligent transfer program is used for moving data from the online databases to the data warehouse. The transfer program collects all information related to a

**Table 8.1:** Selected fields of the machine reel table of the online databases.

| Field | PK/FK | Description |
|---|---|---|
| PhaseReelId | PK | Identification number of the machine reel at this production phase |
| ModuleId | FK | Identification number of the production phase |
| ReelNumber | | Machine reel identification number used in the automation system |
| GradeId | FK | Identification number of the paper grade |
| StartTime | | Time when processing of the machine reel started at this production phase |
| EndTime | | Time when processing of the machine reel ended at this production phase |

PK: primary key, FK: foreign key

machine reel from an online database, and creates a line for each in the machine reel table (see Table 8.2). In contrast with the machine reel table in the online databases, the table in the data warehouse contains information of the production line that produced the machine reel and of the parent reel. More detailed data are stored in a table where each machine reel has a row for each production phase (see Table 8.3), which is essentially a copy of the machine reel table in the online databases augmented with the identification number of the production line, the global identification number of the machine reel, and a quality index value for the current production phase.

### 8.3.3 Application level

Different user interfaces are provided for accessing the measurement and quality index data and for system maintenance. A quality monitoring software is the main access point to the data. The user can select a set of machine reels to work with, and display measurement (Figure 8.4) and index data (Figure 8.5) for these reels. It is necessary to be able to view the profile data in order to interpret the quality variations that are seen in the index data.

**Table 8.2:** Selected fields of the machine reel table of the data warehouse.

| Field | PK/FK | Description |
|---|---|---|
| ReelId | PK | Identification number of the machine reel at the plant |
| LineId | FK | Identification number of the production line where the machine reel was produced |
| ReelNumber | | Machine reel identification number used in the automation system |
| GradeId | FK | Identification number of the paper grade |
| StartTime | | Time when processing of the machine reel started at the plant |
| EndTime | | Time when processing of the machine reel ended at the plant |
| ParentReelId | | If this machine reel was created when another was broken, the identification number of the original machine reel |

PK: primary key, FK: foreign key

**Table 8.3:** Selected fields of the production phase machine reel table of the data warehouse.

| Field | PK/FK | Description |
|---|---|---|
| LineId | FK | Identification number of the production line where the machine reel was produced |
| ReelId | PK, FK | Identification number of the machine reel at the plant |
| ModuleId | FK, FK | Identification number of the production phase |
| PhaseReelId | | Identification number of the machine reel at this production phase |
| PhaseReelNumber | | Machine reel identification number used in the automation system |
| PhaseReelGradeId | | Identification number of the paper grade |
| StartTime | | Time when processing of the machine reel started at this production phase |
| EndTime | | Time when processing of the machine reel ended at this production phase |
| QualityIndexValue | | Quality index for this production phase |

PK: primary key, FK: foreign key

**Figure 8.4:** The profile view of the quality monitoring software. Each pass of the measurement scanner is represented in the view with one row of pixels, newest data being on the bottom. Reel changes are marked with a black line and missing data with gray.

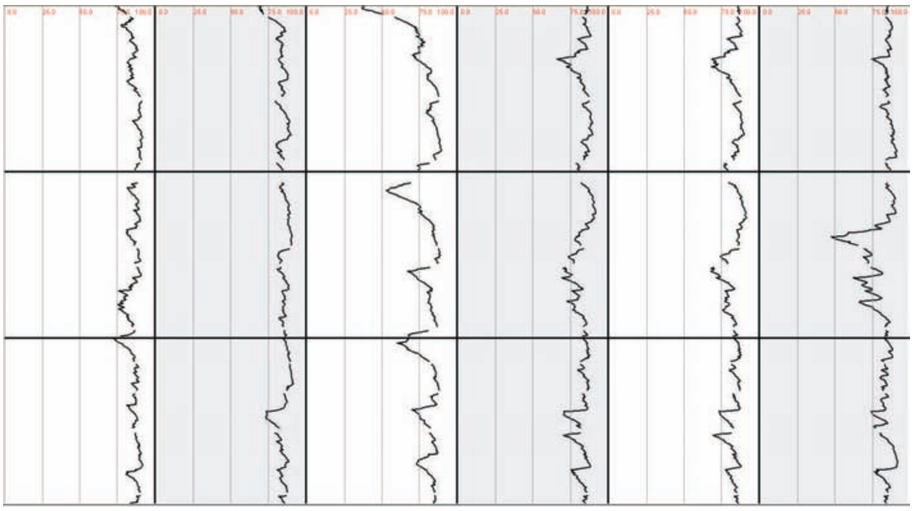

**Figure 8.5:** The quality index view of the quality monitoring software. The figure shows the values of six quality indices for the data shown in Figure 8.4. Good index values are on the right hand side of each subplot.

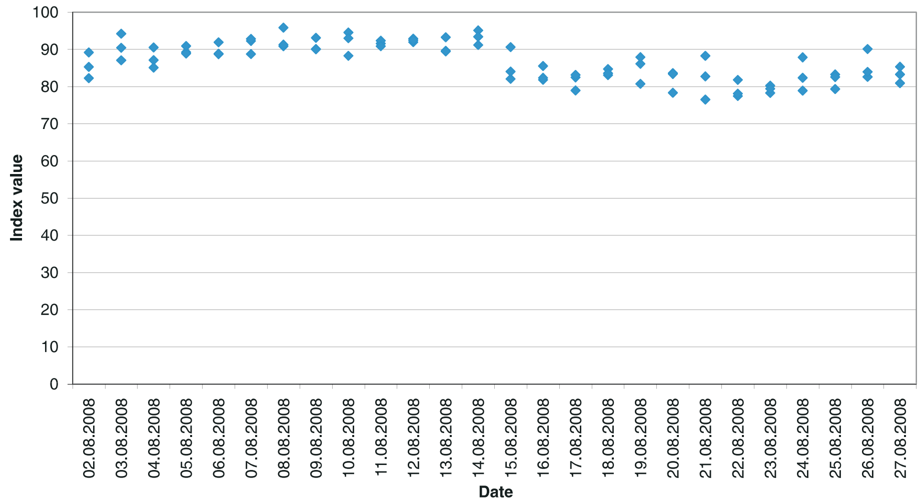


**Figure 8.6:** Top-level quality plot as seen in Excel.

For high-level quality information, a Visual Basic for applications (VBA) application was created. The purpose of this application is to import production line level and plant level quality information to Excel for further analysis and visualization.

To configure the quality assessment system, a maintenance software was developed. With this software it is possible, for instance, to create new quality indices using the existing computation methods and to change the scaling parameters for the indices.

## 8.4 Usage of quality assessment

After the data acquisition system and all the necessary software components were available, a quality index hierarchy was defined. A part of the performance metrics presented in Chapter 4 were utilized, complemented with proprietary metrics already in use at the paper mill. For the paper machine, there are 6 metrics computed for 6 variables, resulting in a set of 36 low-level performance indices. Based on these low-level indices, second level indices were computed for each variable and for each feature using the arithmetic mean as the aggregation function. Finally, a high-level paper machine performance index was computed as the mean of the second level indices for the features. The second level indices for the variables

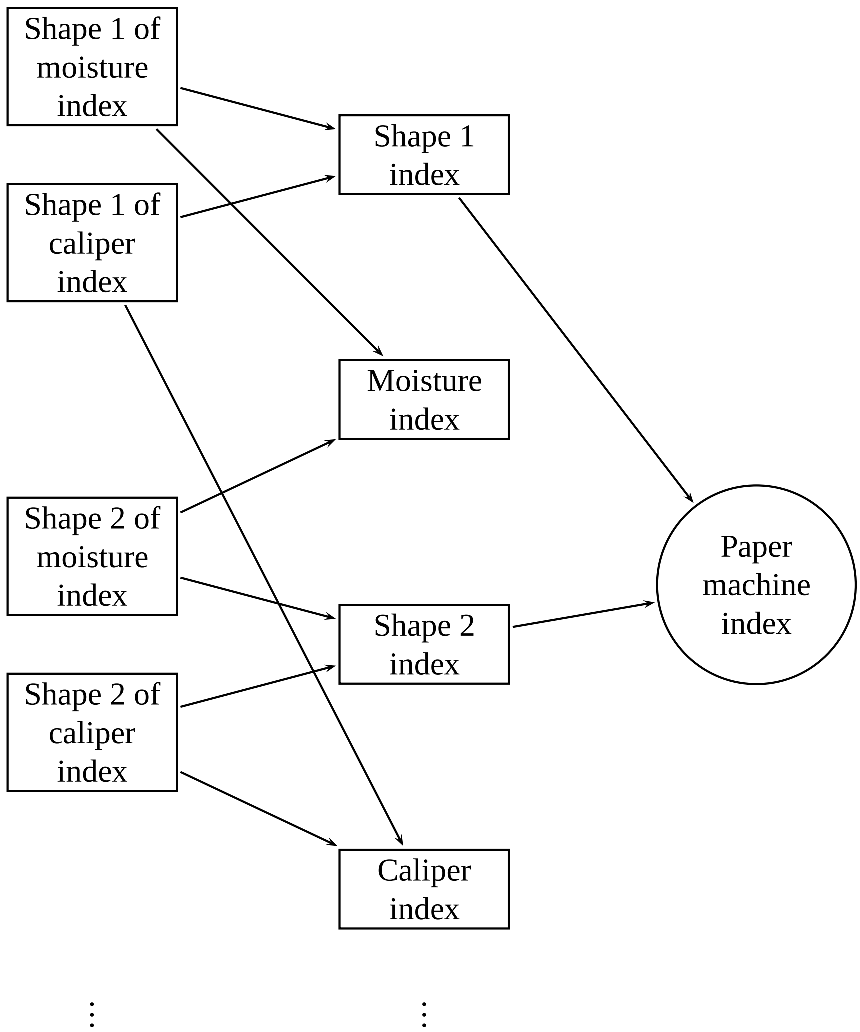


**Figure 8.7:** A part of the index hierarchy developed for a paper machine.

were excluded from the computation of the high-level index because they contain redundant information. On the second level there are 12 indices, and the top-level index consists of 6 second level indices. Figure 8.7 shows a graphical representation of the resulting index hierarchy. For the sake of clarity, only two variables and two algorithms are presented in the schematic.

Figure 8.8 shows an example with paper machine data. Each bar in the figure represents one sample, and the direction of time is downwards. The timespan depicted is about 50 hours. Each subplot contains the time series for one performance index. In each case, the value 100 represents good behavior. Indices from 1 to 4 show different types of variations. Because the indices are sensitive only to one feature, such as the shape of the cross-section, the values of the indices change irrespective

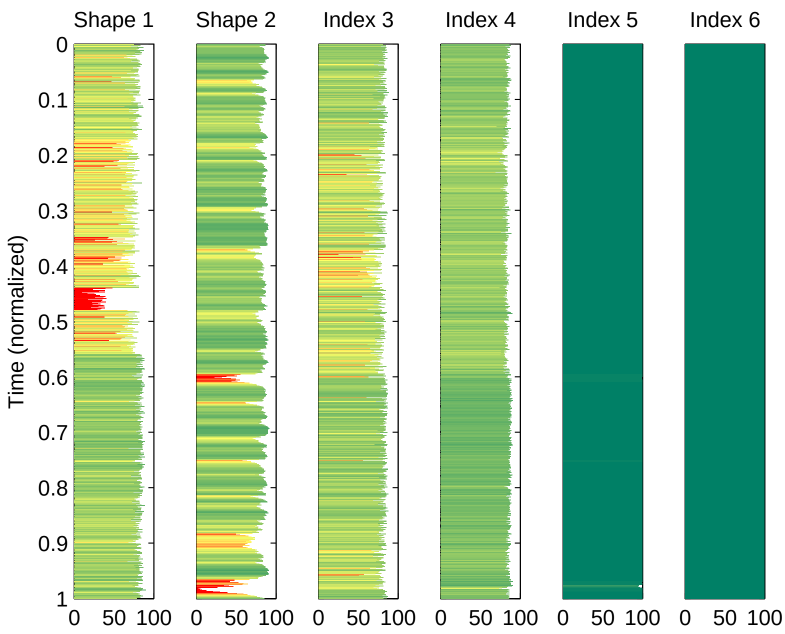


**Figure 8.8:** Low-level moisture index data corresponding to the index hierarchy in Figure 8.7. Each bar represents one sample, and the direction of time is down the page. For each performance index the value 100 is desirable.

of each other. This is the case especially for indices 5 and 6: the performance degrading features they monitor do not appear during this time period.

Figure 8.9 illustrates different methods for combining low-level indices. In this example, all the low-level indices shown in Figure 8.8 are included. Second level indices for different features are shown in Figure 8.10 and the top-level index is shown in Figure 8.11. In both cases, the aggregation methods are arithmetic mean, minimum, and aggregation based on percentiles as shown in Equation (5.23). As expected, the mean averages out most of the variation in the low-level indices, the minimum indicates poorer average performance than the other methods, and the percentile approach is in between the two other aggregation methods. The scaling functions were tuned automatically for each operating point based on the mean and standard deviation of the performance indices. The data used in the tuning was historical data from routine operation.

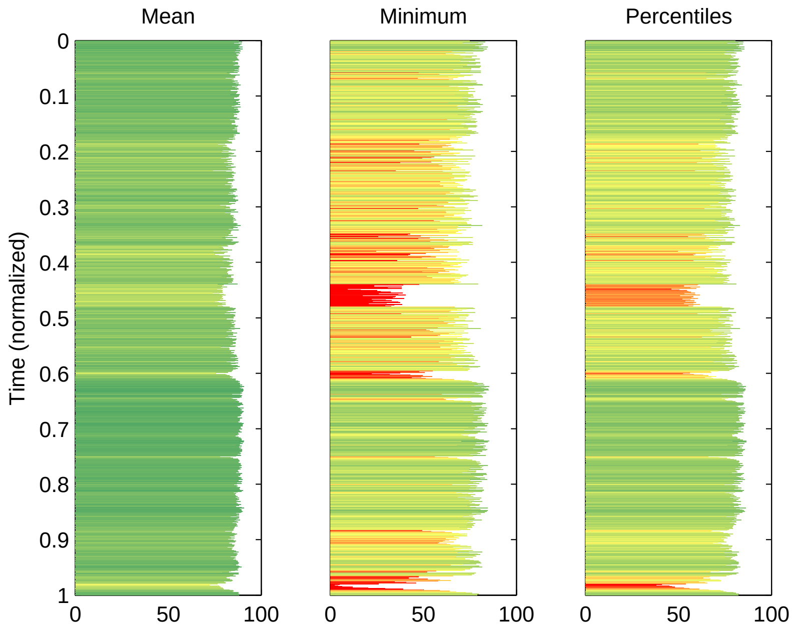


**Figure 8.9:** Demonstration of different aggregation functions for computing the second level shape 1 index corresponding to the index hierarchy in Figure 8.7. Each bar represents one sample, direction of time is down the page. For each performance index the value 100 is desirable.

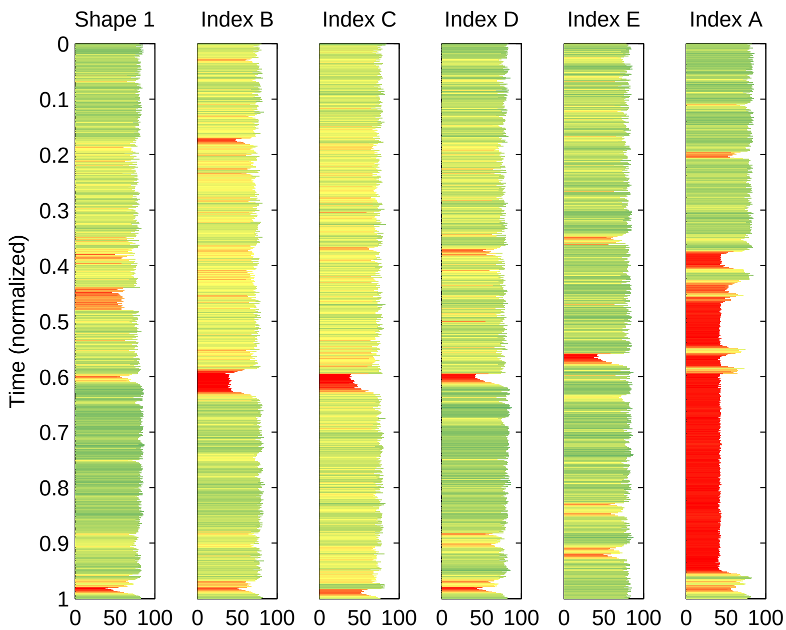


**Figure 8.10:** The second level feature performance indices corresponding to the index hierarchy in Figure 8.7. Percentile aggregation is used in this example. Each bar represents one sample, direction of time is down the page. For each performance index the value 100 is desirable.

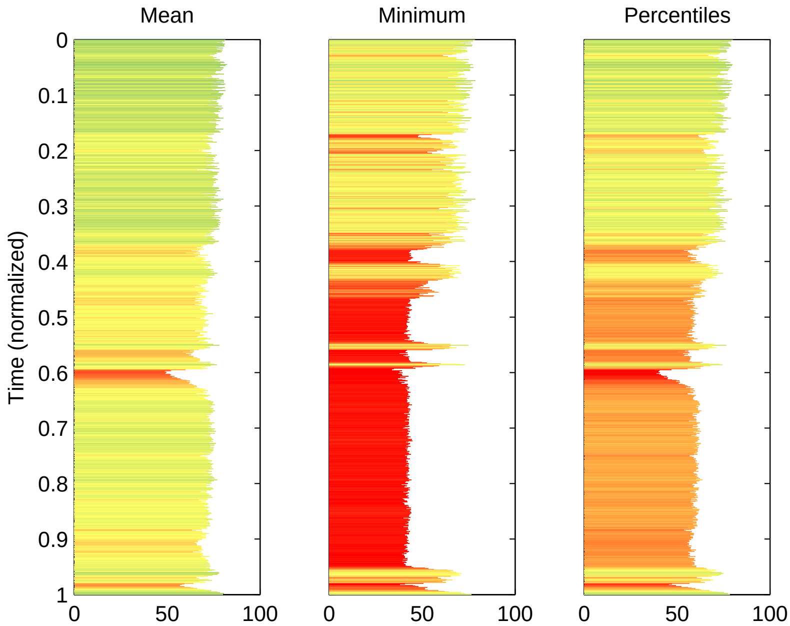


**Figure 8.11:** Demonstration of different aggregation functions for computing the paper machine index corresponding to the index hierarchy in Figure 8.7. Each bar represents one sample, direction of time is down the page. For each performance index the value 100 is desirable.

## 8.5 Discussion

The quality assessment framework described in this chapter is currently running at a paper mill. Before the implementation was done, only a fraction of the available quality information was being used. Quality control was based on the laboratory measurements that were taken from the end of each machine reel.

Once the system was set up, all online measurements became easily accessible in an unaveraged form. The quality indices assess not only the quality of an entire machine reel, but also any given part of the machine reel. Hence, it is possible to find poor regions from reels having all averages within specifications.

When used in performance evaluation of a paper machine, the index framework provides the plant personnel with different viewpoints to performance. The paper machine index gives a useful long-term overview of the performance of the paper machine. Using the second-level indices it is possible to monitor either the performance with respect to the different features or with respect to the different variables. The low-level indices enable a more detailed analysis of the changes in performance.

# 9 Conclusions

The theme of this thesis, assessing the performance of complex industrial plants, has been the subject of many scientific publications since Harris presented the minimum variance index. The literature review part of this thesis presented some of these developments. The multitude of methods justifies the development of the normalized performance index framework presented in Chapter 5. Chapter 4 presented a number of performance indices for two-dimensional web processes, an application area for which such indices were unavailable until now. Implementing performance assessment in practice was a major part of the work leading to this thesis, and is visible throughout the thesis: Chapter 3 discusses the practical issues that must be dealt with when selecting data for a performance assessment system. A simulation example in Chapter 6 showed some properties of widely used performance indices and to create a minimal performance assessment framework. Two large-scale industrial applications were described in Chapter 7 and in Chapter 8.

Evaluation of the performance of industrial plants and subprocesses is imperative in order to guarantee high product quality and economical operation. Advanced methods for performance assessment on device or control loop level exist, but generic solutions for plant-wide monitoring are few due to the complexity of even a small real-world plant.

The first step in performance assessment is to gather valid data from the process. Depending on the age of the equipment this may be very time-consuming, or it might be as simple as a database query. Once the data are obtained, they must be preprocessed to remove outliers and other unusual phenomena. In this thesis several metrics for determining the performance of a control loop were presented. The choice of method depends strongly on the application at hand. Usually there is a need to refine the metrics such that the human operator will get a smaller amount of information, preferably only when there is significant performance degradation detected.

This thesis proposed a performance assessment framework for evaluating individual control loops as well as high-level functions of an industrial production plant. The individual performance indices were scaled to the interval $0\dots100$ for easy interpretation. Different scaling functions were presented, as well as guidelines for choosing the scaling function parameters automatically. Different methods for combining low-level indices into high-level performance measures were shown and compared. Scaling and aggregation use fairly simple mathematics, so it is easy to understand the results given by the performance assessment system.

The main advantage of the proposed approach is that all the indices have the same appearance, i.e., they are scaled to the interval $0\dots100$. Consequently, the user needs not to check the interpretation and the acceptable range for each index, since they are always the same. Additionally, it is easy to combine several indices together into a hierarchical structure. The scaling implies that changes in the operating point and other known disturbances were taken into account in the selection of the set of scaling parameters, and do not affect the performance indices. Device level performance measures are ill-defined if they do not consider this type of plant level phenomena that affect the operation of the device.

This thesis presented two industrial examples to illustrate the proposed framework and to demonstrate its applicability. Since in both cases there was no existing performance assessment system, straightforward comparison between an old and the new system was not possible. Also a change in plant ownership in the paper mill case hindered the evaluation of the utility of the index framework. The examples show, however, that the index-based approach is well-suited for the process industries and that it can substantially help the operator in charge of plant performance. The number of control loops monitored is unimportant, because the indices compress large amounts of low-level information into a few high-level measures. The parameters can be tuned automatically using process data, and retuned in case of changes in the process. Different high-level indices can be created based on the same data to suit the needs of different users.

The downside of any performance assessment system is that the users may learn consciously or subconsciously the procedures that maximize the values of the performance metrics. Depending on the construction of the performance assessment system and on the suitability of the performance metrics, this can have undesirable side-effects, such as excessive energy or material consumption.

The growing demand for more cost-effective operation will increase the number of real-world applications of different performance assessment methods. The development of data acquisition and data processing hardware and software will open new opportunities for novel methods and algorithms. Both practical experience and theoretical research are needed in the near future. Performance assessment implementations are still very application dependent. The index framework proposed in this thesis provides an uniform and generally applicable method of presenting performance data. Future research should address the question of creating more application-independent low-level performance measures.

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# A

# Median filtering

The median of a dataset is the value that is in the middle of the dataset if the data are ordered. If the number of data points is even, the median is the mean of the two values that are closest to the middle of the dataset. Median may be preferable to mean if there are outliers in the data. Outliers affect the mean more than they affect the median.

The windowed median filter uses a sliding window to filter profile measurements. Using a window size of $w$ ($w$ is odd), the filter slides the window along the profile. The filtered value at position $i$ is the median of the values of the positions $i-(w-1)/2 \ldots i+(w-1)/2$. On the edges of the web only the measured data points are used and the window is made smaller to account for the data points that would be outside the web.

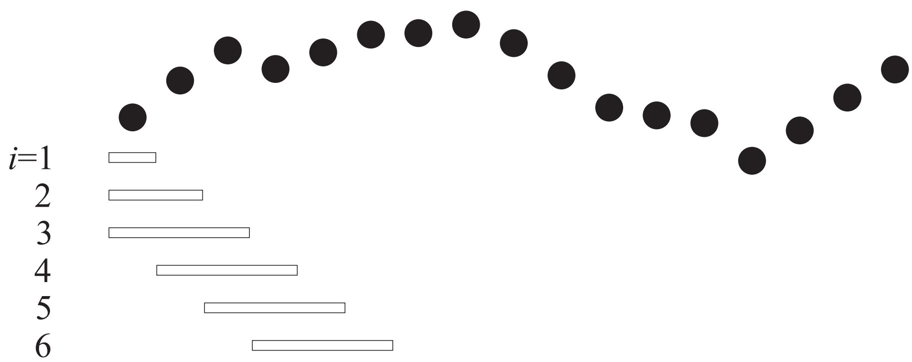


**Figure A.1:** The evolution of the median filtering window at the edge of the paper web. The bar represents the size of the window (nominal size $w = 3$) for $i = 1, 2, 3 \ldots$

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