Research Report D5.2.7.3
Helsinki 2015

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Decision support for risk management in mining industry
MMEA WP5.2.7 Mining
Deliverable D5.2.7.3

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ISBN 978-952-5947-87-8

Cleen Ltd.

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Helsinki 2015

Report title:

Decision support for risk management in mining industry, MMEA WP5.2.7 Report

Key words:

Environmental decision support, risk management, intelligent analysers, adaptation, diagnostics, prognostics, performance monitoring, condition monitoring

Abstract

Keeping up with modern standards and expectations set for mining industry demands constant development of the risk management that is both reliable and transparent. Mining operations concern various stakeholders located inside the vast area of possible effects of mining and this requires accurate planning of risk management. Decision support provide information leading to optimal solution and possibly making operations more open and transparent in the process. This report contributes to the subject as a review of decision support tools and varying methods. It drives to give some insight in the usability of these resources for risk management. Integrated smart systems for risk management can be moved towards real-time operation by combining intelligent analysers with methodologies of risk identification and assessment. Decision support and risk analysis software provide platforms for calculations in special cases. Industrial systems with extensive information require integration with automation systems. In the mining industry, the risk management has two focus areas: (1) water is the main topic in the environmental area, (2) the condition of machines and process devices is important in the mines. The environmental risks are discussed in the risk identification and assessment. The intelligent analysers have been tested in the condition monitoring and integrated with the performance monitoring. The nonlinear scaling can be used for any measurements and open data to develop intelligent indices for control, maintenance and management. Continuous monitoring solutions are under development and their potential is increasing as new applications and ideas form in both environmental and condition monitoring.

Contents

1 Risk management

A careful assessment of possible events that can happen in certain circumstances, allows the controlled risk monitoring and the building of a proper risk management plan. Mine has to make an extensive mapping of risks for human safety, environment, and equipment before its operation is liable. A proper risk management plan minimises the possibility of unexpected events and their impacts. It helps in the mapping of adverse events and detecting them even before they happen. The risk assessment for quantitative risks is done by calculating the probability of an event and the magnitude of its effect, for example, in currency. In qualitative risk assessment the probability of the risk and the effect of the risk is evaluated by describing words such as “high” or “low”. Differing circumstances may have effect on risk probability or severity and need their own evaluation. This report focuses on risks concerning environment, safety, and mining process. Unplanned events in these areas can produce environmental incidents, worker accidents, production losses, or affect the indicators describing the state of the mining company and cause economic losses.

Several data sources, like open data or process measurements, can be combined with modelling to make indirect measurements for risk identification and monitoring. Modelling provides tools for learning from new situations. Real time measurement data combined with modelling brings new important information for creating early warning systems. Localised signal processing is important for monitoring risks concerning machinery condition. Environmental measurements are essential parts of the performance analysis, which provides a basis for the risk identification in the vast mining area. Suitable and proper decision support for certain tasks is a vital base for successful decision making. Human intervention is also important in adaptation and decision making.

The risk management plan helps in risk mitigation by including the ways for addressing with the adverse events. When a certain measurement or other indicator shows increasing risk levels for an unwanted event, the preventive actions can be started in advance for effect mitigation and risk control. In order to keep the risk assessment up to date, the risks must be inspected very thoroughly and updated frequently for possible changes. Previously occurred incidents can give valuable and accurate information for risk management. Some risk management ways are:

- Eliminating the risk if possible. However one risk is often replaced by another.
- Transferring the risk for example to insurance company.
- Retaining the risk and paying when harm arises.
- Reducing the risk, which is the most common way of risk management. (EEA 1999)

Risks can be reduced by adapting the operation with operating conditions. Figure 1 presents an overall framework for introducing increasingly integrated automation solutions for mining industry decision making and risk assessment. The key in risk management is to focus on real-time operation extended with model-based intelligent analysers, which use measurements and open data for process control and decision making. New indirect measurements are directly useful in the diagnostics and risk analysis. High-level control is essential in adapting the control to appropriate operating areas. The adaptation is partly based on domain expertise. Performance analysis and environmental measurements come up with unknown phenomena for the situational awareness needed in the risk identification. Trend analysis and model-based predictions are important in this. Solutions to combine measurement technology with intelligent analysers for forecasting environmental impacts are addressed in (Juuso and Koistinen, 2015).

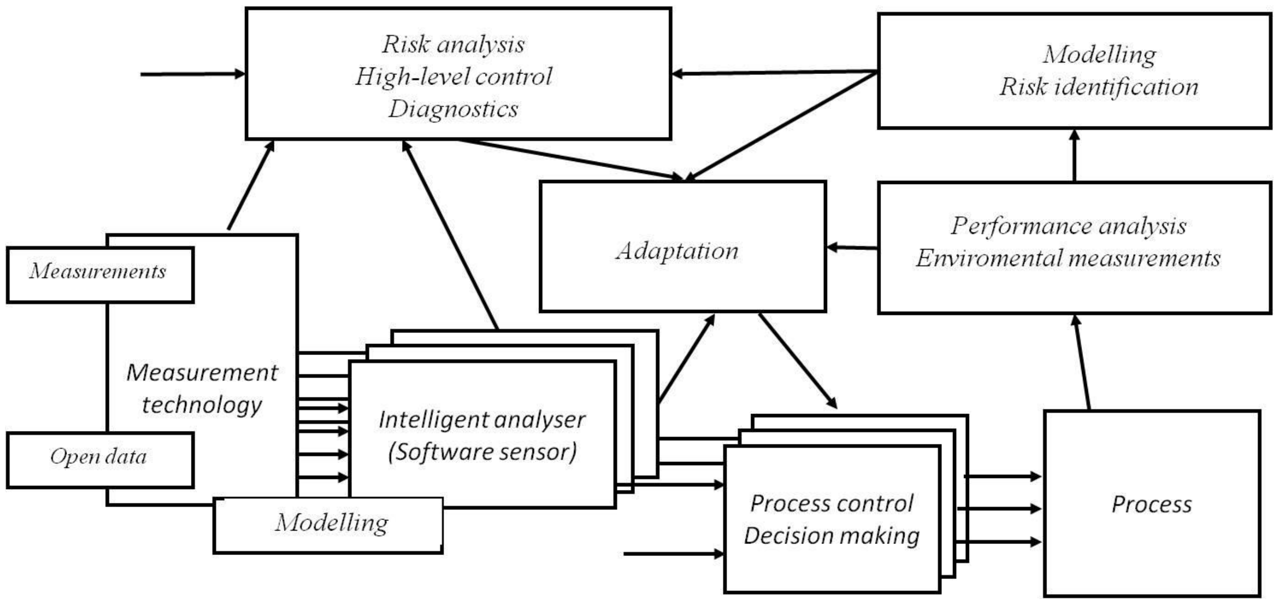

Figure 1. Risk management based on monitoring, control and diagnostics. (Keskimölö et al. 2014)

This report focuses on the integration of intelligent analysers (software sensors) with risk identification and analysis. Chapter 2 addresses on multiple information, methodologies of risk identification and assessment to risk-based decision making with emphasis on environmental problems. Some software tools for decision support and risk analysis are discussed in Chapter 3. Development of intelligent analysers based on models, signal processing, feature extraction and nonlinear scaling are summarised in Chapter 4. Integration intelligent analysers with diagnostics and prognostics is in Chapter 5 presented as a framework of an integrated smart system. The overall solution is summarised in Chapter 6.

2 Risk identification and assessment

Risk analysis starts with the identification of possible problems and hazards continuing with the analysis of the harm to complete systematic risk assessment. Decision support is based multiple information, which combines data and expertise on complexity interactions, changes, material flows and the life cycle of the system. Wireless sensor networks provide new possibilities. Both the environment and the industrial system need to be taken into account in risk identification in the mining industry. Multiple criteria need to be taken into account in the risk-based decision making.

2.1 General methodologies

Present-day risk identification and assessment can use several methodologies for aid. Risk assessment for health and safety has several tools developed, such as FMEA/ FMECA, HAZOP, WRAC, SLAMs, JSA, JHA, Take 5, Bow Tie, to name a few. Some of these tools can be used for equipment or environment related risks as well. These methods are based on consequence and occurrence matrices and have been widely used in every field of industry. The problem with these matrices is that they can easily become too complicated for outsiders to read. (Jim Knowles Group 2010)

Hazard and operability study (HAZOP) is an examination of planned and existing process or operation in order to identify problems that may possess a significant risk to personnel or equipment or prevent operation. HAZOP has conventionally been used in chemical engineer, such as gas & oil industry, but later on it has been extended to withhold complex plants like nuclear reactor controlling and to use software to record deviation and occurrence. HAZOP is a qualitative technique based on guide words and multidisciplinary team. (Jim Knowles Group 2010)

Failure Mode Effect Analysis (FMEA) is one of the first systematic techniques for risk analysis. It is also the most frequently used risk assessment method in evaluating the risks of mining. In FMEA, each mode of failure by the component is assessed for its severity, occurrence, and detection. (Jim Knowles Group 2010)

Workplace Risk Assessment and Control (WRAC) has been the most popular probability/consequence risk matrix method of identifying and prioritising in the mining industry of Australia for the past 20 years. According to studies, WRAC has been fairly successful in decreasing accidents in Australian mine industry. (Jim Knowles Group 2010)

It is not necessarily mandatory to use one single method only since one can fit the best aspects of two or more methods for the case in hand in a new analytical approach. Lapland University of Applied Sciences, Operation and Maintenance research team implemented PDA (Production Deviation Analysis) which united the best aspects of HAZOP and FMECA into a new optimised method. The PDA lists critical events in production failures that could cause safety, environmental, and financial risks and assess the severity of faults and propose corrective measures. For most severe faults, the OIE (Overall Information Efficiency) calculation is recommended for review. OIE helps in identifying critical data sources for early damage prevention and minimisation by optimising big data. (Rauhala et al. 2014)

The terms connected to risk assessment are the risk and hazard, which do not have the same meaning. After risks are assessed, actions can be taken for controlling and minimising them. Short descriptions of terms below (EHSC 2013).

Hazard

Potential of some substance, machine, energy form, condition, situation, practice, or behaviour to cause harm.

Risk

Likelihood or possibility that the hazard will cause harm combined the severity of the consequences.

Risk assessment

Risks associated with each of the identified hazards are assessed for understanding the nature of the risk, including the nature and the severity of the harm and the likelihood of this occurring. Risk assessment includes identification, analysis, and evaluation of risks.

Risk control

Eliminating the risks as far as is reasonably practicable. If risk cannot be eliminated, it needs to be minimised within reasonable limits.

Monitoring and review

Identified hazards needs to be monitored and reviewed along with the assessment and the control processes.

2.2 Environmental risk assessment

A common concept used with the environmental risk assessment is the source – pathway – receptor. The source can be, for example, contamination or leakage. Pathways could be, water, soil, or food chain. Receptors include people, animals, ecosystem, plants, infrastructure, or similar. In this model, the pathway(s) connecting the hazard and the receptor is investigated. When there is no pathway, there is no risk and when a pathway exists, the consequences must be determined. A general model for environmental risk assessment was presented in “Environmental Risk Assessment Version 2” report by the Working Party of the Environment, Health and Safety

Committee (EHSC) of the Royal Society of Chemistry (EHSC 2013). It includes five steps explained below:

1. Hazard identification:
   Property or situation leading to harm.
2. Identification of consequences:
   Related to a certain hazard.
3. Estimation of the magnitude of the consequences:
   Consideration of the spatial and temporal scale of the consequences and the time to onset of the consequences. With chemicals, this step can be called release assessment.
4. Estimation of the probability of the consequences:
   Presence of a hazard, the probability of receptors being exposed to a hazard, and the probability of harm. Step can also be called as exposure assessment or consequence assessment.
5. Evaluating the significance of a risk:
   Product of likelihood of the hazard being realised and the severity of the consequences. May also include uncertainty associated with both the hazard and the risk. Step can also be called as risk characterisation or risk estimation. (EHSC 2013)

Many environmental management tools have difficulties in using the basic scientific data on toxicity, ecotoxicity, fate and transport models, and exposure models. Problems arise from uncertainties in data. Substances can be assumed to be harmful until proven safe or vice versa. One precautionary approach is to do as much as possible to reduce the emission of the agent potentially causing a serious environmental risk before scientific proof of causation. A risk based approach would be to do as much as is necessary to achieve an acceptable risk. (EEA 1999)

2.3 Environmental decision support

Jordan and Abdaal (2013) presented a group of decision support tools for solving environmental problems in the mining complex. These tools were selected by using two preconditions: environmental decisions can be directly based on their results and they address the problem in its integrated complexity. Methods meeting these conditions were landscape ecology (LsE), industrial ecology (IE), landscape geochemistry (LG), geo-environmental models (GEMs), environmental impact assessment (EIA), environmental risk assessment (RA), material flow analysis (MFA), and life cycle assessment (LCA). The combination of several methods should be used because one system cannot address all of the environmental problems in mining. All of these methods aim to link the socio-economic and natural sciences in environmental decision support. Decision support includes data analyses, preference modelling, simulation, visualisation, interactive techniques, and tools such as decision support systems, multiple-criteria modelling, group decision support and meditation systems, expert systems, and databases and data warehouses for aiding decision makers. (Jordan & Abdaal 2013)

Descriptions for tools listed can give some insight about the use and benefits of these methods and references provide more detailed information on tool and its use.

Environmental Impact Assessment (EIA), established in the United States in 1969, is a global tool of accountability that is used widely around the world. The information provided by EIA is considered within a political decision-making arena. It does not necessarily prevent actions with significant environmental impacts from being implemented, but rather authorises these actions in full knowledge of their environmental consequences. One possible frame for EIA process is:

1. Consideration of alternative means of achieving objectives.
2. Designing the selected proposal.
3. Determining whether an EIA is necessary in a particular case (screening).
4. Deciding on the topics to be covered in EIA (scoping).
5. Preparing the EIA report (describing the proposal and the environment affected by it and assessing the magnitude and significance of impacts).
6. Reviewing the EIA report to check its adequacy.
7. Making a decision to the proposal, using the EIA report and opinions expressed about it.
8. Monitoring the impacts of the proposal if it is implemented. (Wood 2003) (Li 2009)

Landscape ecology (LsE) helps in resolving how changes in land use affect plants, animal populations, and planning of human settlement for example. (McGarigal 2010)

Landscape geochemistry (LG) resembles much LsE but differs in how it focuses attention on all aspects of the behaviour of chemical entities (e. g. isotopes, elements, and ions), in both living and dead matter in landscapes of all kinds. Landscape geochemistry focuses on the interaction of the lithosphere with the hydrosphere, atmosphere, and biosphere. (Fortescue 1992)

Industrial ecology (IE) aims in taking tolerances and the characterisation of natural systems in account of creating efficient industrialisation pattern. It views industrial systems in connection with the nature and follows the whole life cycle of the material. (Basu & Van Zyl 2006)

Geo-environmental models (GEMs) are defined by Plumlee & Nash as *"A compilation of geologic, geochemical, geophysical, hydrologic, and engineering information pertaining to the environmental behavior of geologically similar mineral deposits (a) prior to mining, and (b) resulting from mining, mineral processing, and smelting."*. The models can be used to provide impartial geoscience information that can be used to better understand, anticipate, minimize, and remediate the environmental effects of mineral deposits and mineral resource development. (Plumlee & Nash 1996)

Environmental risk assessment (ERA) is a process for estimating the likelihood or probability of an adverse outcome or event due to pressures or changes in environmental conditions resulting from human activities. It can be used to help EIA in addition to risk management. (Ministry of Environment, Lands and Parks 2000)

Material flow analysis (MFA) is a systematic assessment of the flows and stocks of materials within a system defined in space and time. It is a model on how chemical, compound or material takes through the natural and economic cycle. MFA is an appropriate tool to investigate the flows and stocks of any material-based system and it can also be used in IE. (Brunner & Rechberger 2004)

Life cycle assessment (LCA) is a holistic environmental assessment tool that allows the compilation and evaluation of the inputs, outputs, and potential environmental impacts of a product or service throughout its life cycle, from cradle to grave (i.e., from resource extraction and transformation to final disposal, including production and use stages). (Lesage et al. 2008)

The optimal way of solving environmental decisions may lie in using a tool which includes both numerical computations for detailed engineering and intelligent systems for the logical analysis and reasoning tasks. Environmental Decision Support Systems (EDSS) can link quantitative models with the qualitative approach. (Turon et al. 2006) EDSS integrate the evaluation of highly complex and interrelated physiochemical, biological, hydrological, social, and economic aspects of environmental problems. The term decision support system is hard to describe unambiguously because it is a very broad concept and definitions can vary depending on an author. (Obropta et al. 2008) Generally, it can be defined as an interactive, flexible, and adaptable computer based information system especially developed for supporting the recognition and solution of a complex, poorly structured or unstructured, strategic management problem for improved decision-making (BfG 2000). Modern EDSS contains geographical information systems (GIS) functionalities for improving decision maker performance (Matthies et al. 2007). McIntosh et al. collected the insights of several EDSS developers for creating best practices for EDSS tool development so that the future tools can be used effectively for environmental management and that they are likely to be adopted and used (McIntosh et al. 2011). Environmental decision making should be collaborative instead of adversarial. Decision makers should involve or inform the people who must live with the decisions. EDSS can be a tool for making the process more open and transparent in addition to finding optimal solution. Intelligent EDSS or IEDDS can be in a key role in this interaction between humans and ecosystem since they are tools designed to cope with the multidisciplinary nature and high complexity of environmental problems. More about IEDDS can be found in the article *"Intelligent Environmental Decision Support Systems"* by Sànchez-Marrè and others. (Sànchez-Marrè et al. 2008)

Klug and Kmoch presented a framework that uses field observations for real time decision support. Their study used wireless sensor networks and standardised web services for describing near real time indicator processing and Early Warning System (EWS) as an application example where real time data and models are combined. Information is collected from field sensors to sensor nodes from where it is sent to a web service. Users can retrieve data from web service manually (pull based) or information can be distributed directly to users via SMS, email or other messages (push based). Hydrological EWS characterising present situation and predicting likely future scenarios can be used as a DSS for managing water balances for abnormal long rain periods or in short term basis aiding in crisis on hand or expected soon. (Klug & Kmoch 2015)

2.4 Risk-based decision making

Scientific investigations should be used as an aid in risk-based decisions concerning environmental protection and restoration. On the other hand, the public perceptions and socio-economic considerations can effect greatly on decision making regardless of scientific proof. (Younger et al. 2004)

Typical economic cost-benefit analyses are not suitable for analysing broad mining complexes. Multiple-criteria decision making (MCDM) methodologies allow the accounting of environmental costs in company decision-making in addition to technical aspects, costs, social aspects, and the company image before the society. Freitas and Magrini (2012) presented a MCDM model for including environmental aspects in decision making and its use in their article “Multi-criteria decision-making to support sustainable water management in a mining complex in Brazil”. The model included the image criterion as a part of the social aspect for its importance in decisions related to water management. (Freitas & Magrini 2012) Multiple-criteria decision analysis (MCDA) or MCDM methods are often linked to Geographical Information System (GIS) to include geographical dimension for spatial decision problems (Massei et al. 2014).

Complex MCDM systems can have the large sets of data which is difficult to process. Classification algorithms can be used to identify the most effective variables from this data. Preprocessing the data with data mining tools can be useful for speeding up the calculation by reducing and organizing the variables. (Mosavi 2010)

Case-based reasoning (CBR) is a problem solving paradigm for finding out the solution to a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation (Aamodt & Plaza 1994). CBR can be understood as reasoning by remembering. From a structural point of view CBR is a cyclical method that stresses the reuse of solutions to similar problems, where solutions are maintained in a carefully indexed memory. Cases are represented by models: the risk level of web breaks in paper machines used several case-based models for different break sensitivity categories (Juuso & Ahola 2008).

3 Software tools

Decision support systems integrate general methodologies into specialised applications. Risk analysis tools take into account uncertainties of the complex information. These issues are closely connected with the software tools.

3.1 Decision Support Systems (DSS)

Some software tools have been developed for supporting decision making by enabling the use of several assessment and support methods.

The DecisionTools Suite is a software suite with the integrated set of programs for analysing risks and uncertainty in a wide variety of industries. It can be used to perform single quantitative analyses with individual programs or by combining several analyses for more complete results. The DecisionTools Suite includes optimisation, decision trees, what-if analysis, data analysis with neural and statistical methods. The whole package is integrated into Excel spreadsheets. (Palisade)

The Environmental Effects Monitoring (EEM) Statistical Assessment Tool (SAT) Decision Support System (DSS) is a tool for studying the effects of industrial or other effluents on fish and benthic populations. EEM-SAT DSS is a rule-based expert system, which links test datasets with reference datasets and determines the magnitude of each endpoint effect. It was developed for the federal environmental effects monitoring program of Canada for the pulp and paper and mining industries. (Booty et al. 2009)

The E2 (WaterCAST from 2008) is software for modelling catchment water scenarios. The river system is modelled with node-link structure and catchment is represented by sub-catchments containing functional units. The sub-catchment delivers flow and constituents to a node. The E2 software has been included in the Catchment Modelling Toolkit (Now called eWater Toolkit (eWater)) since 2005. It has been used to construct over 20 specific DSS across water quality and environmental management domains that include bushfire impacts, land use planning, climate change, adoption of the best management practices, and peri-urban development. (Argent et al. 2008)

Spatial Analysis and Decision Assistance (SADA) focuses on environmental remediation and incorporates spatial assessment tools in analysis. Software has modules for geographical information systems (GIS), visualisation, geospatial analysis, statistical analysis, human health and ecological risk assessment, cost/benefit analysis, sampling design, and decision support. It has an easy way of distributing information to assessors and decision makers with ".sda" –file and the program is freeware so the information is easily viewable by all the relevant people. (Stewart & Purucker 2011)

3.2 Risk analysis

In risk analysis, the concept of probability comes up and it needs to be determined. The Risk analysis of uncertain systems can be studied with Monte Carlo simulation (random number generator) done with software tools. There are multiple software providers offering tools for this type of calculations: this section presents two software tools, Goldsim and @Risk, which are frequently used in engineering.

GoldSim – Environmental Systems Modelling and Risk Assessment tool (Goldsim)

GoldSim is software developed to support decision and risk analysis by using Monte Carlo simulation to predict future performance while quantitatively presenting risks and uncertainty. The software is widely in use in business, engineering, and science applications. In engineering, GoldSim has been used in the risk analysis, reliability, and failure analysis of mines, power plants, space crafts, computer networks, and defence systems. (Goldsim)

GoldSim also has a modelling suite of environmental systems, which finds frequent use in mine water and waste management, human health risk assessment, and ecological modelling. An example of ecological model is presented in Figure 2 illustrating a model used to forecast the impact of different water projects on salmon population in the state of California, USA. (Goldsim)

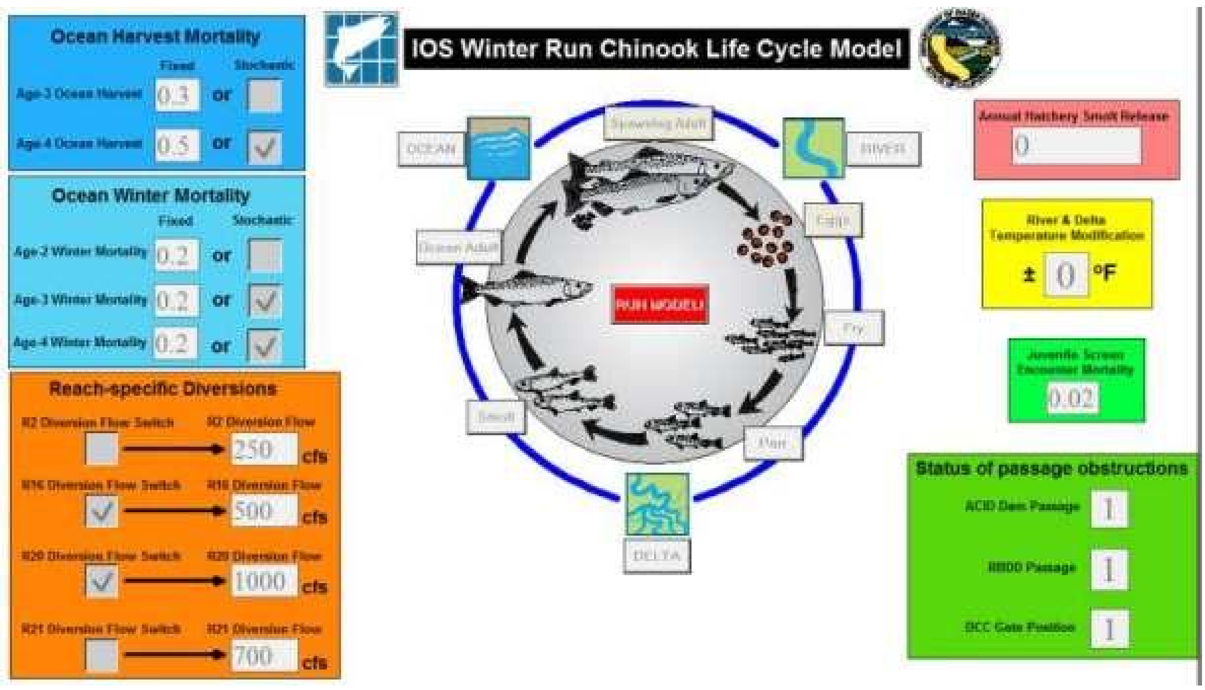

Figure 2. GoldSim salmon life-cycle model. (Goldsim)

@Risk – Risk Analysis Software (Palisade)

@Risk is risk analysis software that uses collected Excel spreadsheet data (Figure 3) to calculate the possible outcomes and likelihood of each outcome using Monte Carlo simulation. It can be used to replace uncertain cell values in spreadsheet with selected probability distribution functions to simulate numerous possible scenarios. @Risk is included in The DecisionTools Suite. (Palisade)

@Risk can be used in various different areas like in Six Sigma quality analysis or in project management to predict risks in cost estimation and project scheduling. It also has a tool for risk management strategies which helps in the resource allocation, optimal asset allocation, scheduling, and more. (Palisade)

@Risk is widely used in several areas of industry like finance, security, energy, manufacturing, medical, environment, defence, and aerospace. Environmental uses have been in the preservation of endangered species and pollution clean-up and projections. Industrial uses have been in analysing quality, product or product life cycle, and production siting or shutdown. (Palisade)

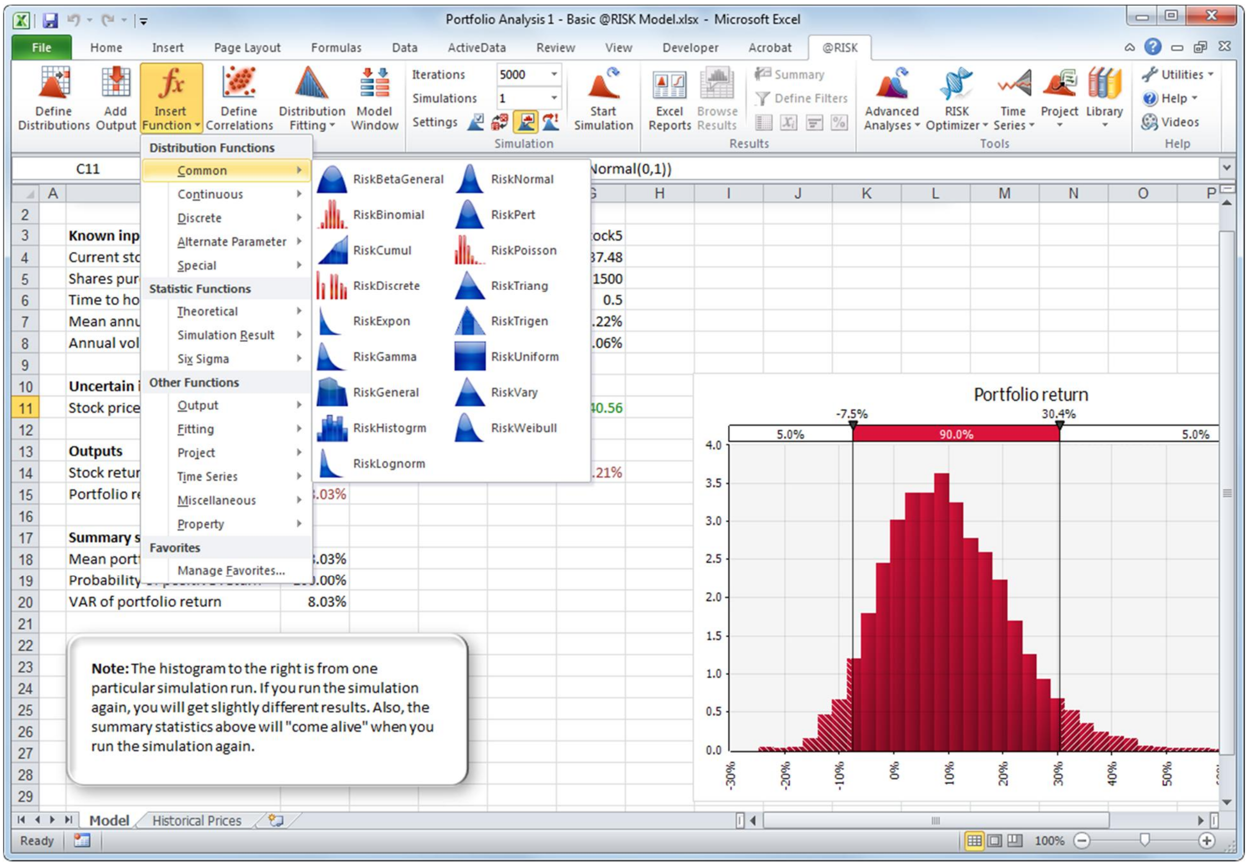

Figure 3. @Risk analysis tool as an excel add-in. (Palisade)

4 Intelligent analysers in risk analysis

Fault detection is important in the risk analysis of machines and process devices. Faults can arise from many causes; for example, errors made in design or assembly, wrong operation, lack of maintenance, corrosion, aging, wear during normal operational conditions, or external agents, like noise, disturbance, human errors, etc. Fault detection is usually seen as a part of the supervisory level in mill-wide control systems. In the early days of distributed control systems, the fault detection was mostly based on certain limits of numbers, but today, fault detection and diagnostics is performed by means of the advanced techniques of mathematical modelling, numerical analysis, and signal processing identification methods. These intelligent computational methods provide the high-level decision support system for scheduled, preventive, and predictive maintenance. (Fortuna et al. 2007; Lahdelma & Juuso 2011a)

Fault symptoms can be abnormal deviations of measurements or interactions represented by models (Frank 1990). Features extracted from waveform signals and intelligent indices provide highly useful information on faulty situations (Lahdelma & Juuso 2011a; Lahdelma & Juuso 2011b).

4.1 Soft sensors in fault detection

Different kinds of faults can occur in a system. Like systems, faults can also be mathematically modelled (Figure 4). Modelling faults can be useful in developing effective fault diagnostic tools, especially when they are based on the mathematical model of the system. Once the model of the fault-free system has been developed, determining models for the most common faults can lead to the development of mathematical models for the faulty system. This is done by studying the effects of the mathematically modelled faults on the system model equations. (Fortuna et al. 2007)

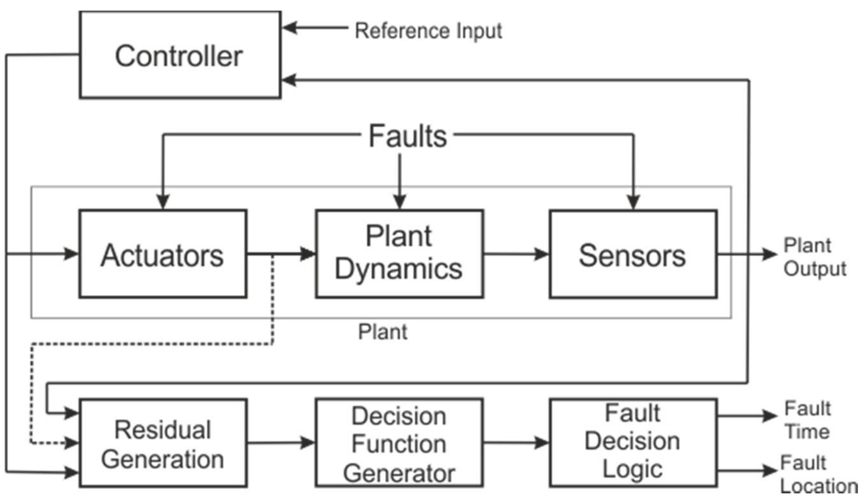

Figure 4. Conceptual scheme for model-based fault detection introduced by Frank (1990).

The soft sensors are derived from the pre-determined indices of fault symptoms, which are usually abnormal deviations from pre-known physical measures of quantity, velocity, or temperature, for instance. The fault symptoms can be recognized from the abrupt, drifting, or intermittent changes of process variables. Soft sensors can also work parallel with hardware sensors as fault diagnostic tools enabling the realization of more reliable process control. (Fortuna et al. 2007)

Sensor validation is a particular kind of fault detection, where the monitored system is seen as a single or a set of sensors. At the most basic level, the aim of sensor validation is to provide the users of the measurement system with an evaluation about the reliability of measurement. The sensor validation system may provide an estimate for the measurement, whereas the actual sensor is out of order. This way, the soft sensors can be paralleled with actual sensors, and faults can be detected by comparison between the outputs of actual and soft sensors. Secondly, the soft sensors can be used as a back-up device once a fault has been detected. (Fortuna et al. 2007)

4.2 Signal processing and feature extraction

To detect machinery faults at early stage, the advanced signal processing methods are needed and the using of higher derivatives can increase the sensitivity of fault detection. Signal processing and the using of higher derivatives are addressed in (Lahdelma & Juuso 2011a). Few applications with the functionality of higher derivatives are presented in (Lahdelma & Juuso 2011b). Generalised spectral norms include information about the frequency content (Karioja & Juuso 2015).

4.3 Intelligent indices

Dimensionless indices are derived from the known characteristics of mechanic faults that can be used to predict the failure of equipment. The condition indices detect differences between normal and faulty conditions and provide sufficient information on the severity of faults. Several measurements can be combined to form a single condition index in order to acquire more information for fault detection. Continuous and periodic condition monitoring measurement data can be scaled to linguistic levels and used in the forming of condition and stress indices after signal processing and feature extraction (Figure 5). The automation system can handle condition and stress indices as normal process measurements.

The real measurement values can be scaled using nonlinear scaling to form a practical basis for modelling nonlinear multivariable systems with linear methodologies (Figure 5). The scaled values show the measurement levels in an understandable way. Linguistic equation (LE) systems use nonlinear scaling based on generalised norms and moments (Juuso & Lahdelma 2010; Juuso

2013). Linguistic equation (LE) models of the normal case are suitable for detecting fluctuations, and case-based reasoning (CBR) is used if specific case models are developed. The overall procedure includes the following steps: (1) select informative features, (2) scale the features, (3) calculate intelligent indices, and (4) combine indices in models (Juuso & Leiviskä 2010).

Intelligent indices can be used as a stress index for studying the severity of the load (Juuso & Ruusunen 2013). Contributions of stress have also been studied for a loading machine in an underground mine (Koistinen & Juuso 2015a). The compact solutions facilitate the on-site calculations of high frequency vibration measurements for maintenance and operational monitoring (Koistinen & Juuso 2015b). The scaled values can be directly used in the intelligent trend analysis introduced in (Juuso 2011a). Nonlinear scaling is suitable for finding control limits to generalise statistical process control (Juuso 2015a).

Possibility of a recursive data analysis is important in the prognosis where new phenomena activated with time considerably change the models (Juuso 2015b). Fatigue and the lifetime for specific materials can be evaluated with Wöhler curve or S-N curve generated from material tests. The curve presents the magnitude of a cyclic stress (S) against the logarithmic scale of cycles to failure (N). The S-N curves are represented by linear interactions and intelligent stress indices make the calculation of cumulative contributions highly efficient (Juuso & Ruusunen 2013, 2015).

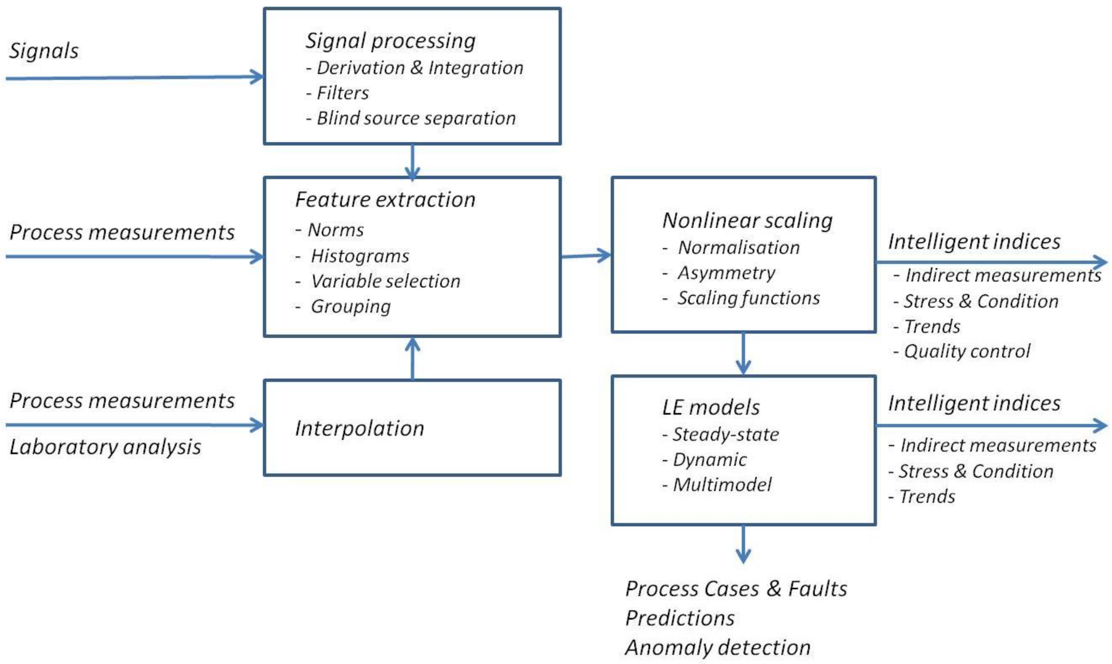

Figure 5. Nonlinear scaling in development of soft sensors (Juuso 2013).

5 Integrated smart system

Process control and intelligent condition monitoring should be combined to achieve efficient risk management (Juuso & Galar 2016). Continuous condition monitoring (CM) provides informative indirect measurements: stress indices are aimed for stabilising control; condition indices are useful in optimising and coordinating control (Figure 6). Continuous and periodic CM measurements are used together with process measurements and laboratory analysis in diagnostics and prognostics, which provide important additional information for the adaptation of control strategies. (Juuso & Lahdelma 2013; Juuso 2013) Diagnostics and prognostics are even more important for control than for maintenance. Automation systems provide good platforms for the risk management systems.

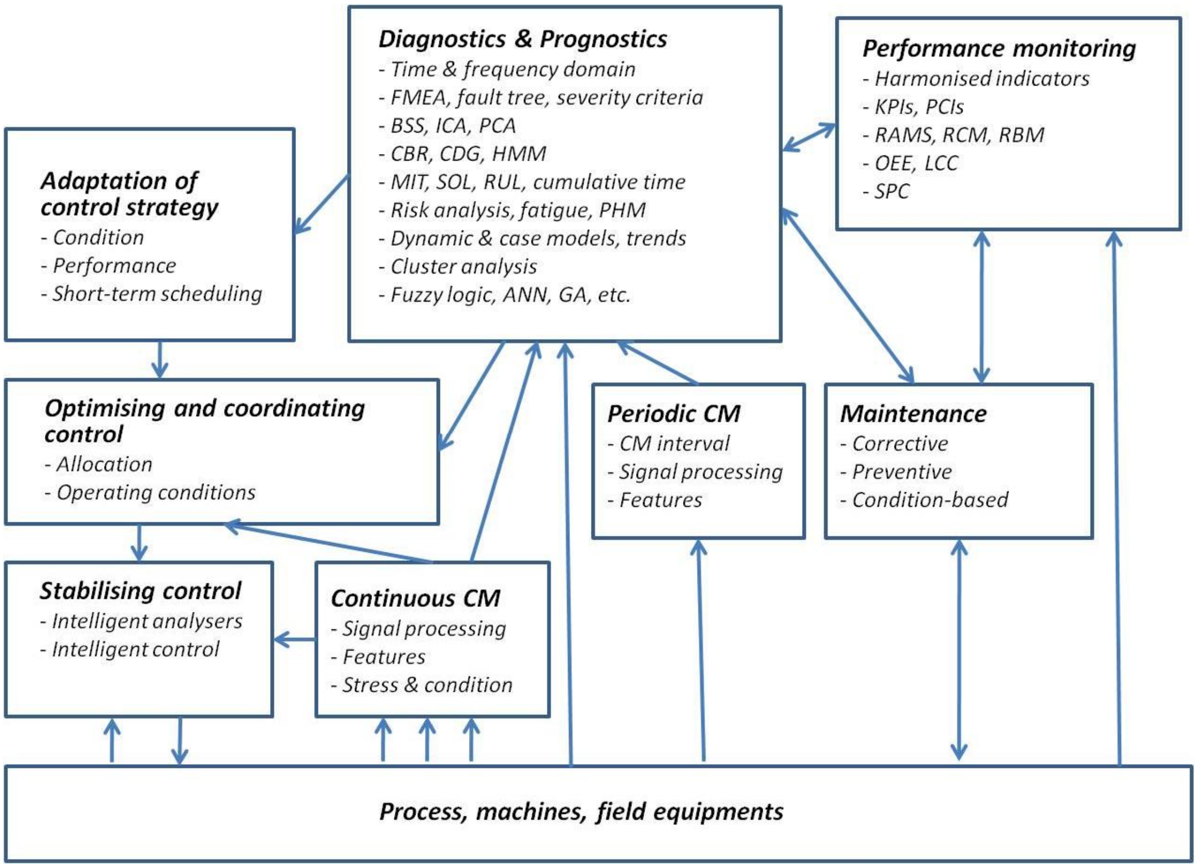

Figure 6. Integrated control and condition-based maintenance (Juuso 2013).

The costs of transferring and storing the measurement data can be lowered by data compression. The piecewise linear regression can be used for the data compression. When using intelligent sensors, the amount of measurement data can be very large and it can be reduced by using a combined analogue and digital data processing technique. (Lahdelma & Juuso 2011b). Nonlinear scaling is used for condition monitoring measurements (Juuso & Lahdelma 2013) and process measurements (Juuso 2013). The scaling functions can be updated recursively (Juuso 2015b). Slow changes can be detected with trend analysis (Juuso 2011) and used in prognostics (Juuso & Lahdelma 2011, Juuso 2015b).

The nonlinear scaling approach is suitable for performance monitoring with various stress, condition and health indices as inputs. Similar approaches can be used for outputs: quality indices, harmonised indices, key performance indicators (KPIs), process capability indices (PCIs), life cycle cost (LCC) and overall equipment effectiveness (OEE). The analysis can be further deepened with LE modelling since all the indices are in the same dimensionless range [-2, 2]. (Juuso & Lahdelma 2013). Generalised statistical process control (GSPC) is directly useful in demonstrating possible risks (Juuso 2015a). The analysis can be extended with widely used systematic approaches: RAMS (reliability, availability, maintainability and safety) analysis is the basis of the reliability centered maintenance (RCM) and the most appropriate maintenance plans can be determined by risk-based maintenance (RBM).

The key of the risk management is in detecting deviations and anomalies by using advanced features and intelligent indices in diagnostics and prognostics (Figure 6). FMEA and fault trees are common methodologies. Real-time measurements are essential in developing severity criteria, dimensionless indices MIT and SOL and intelligent indices in time domain analysis, which can also include frequency content. Combinations of signals are important in blind source separation (BSS), independent component analysis (ICA) and principal component analysis (PCA). Applicability of process measurements and laboratory analysis can be enhanced with feature extraction and nonlinear scaling (Figure 5).

Proportional hazard models (PHM) are used in prognostics to estimate the remaining useful life (RUL). The combinations of exponential models are transformed into LE models by using recursive nonlinear scaling. In the fatigue analysis, the stress contributions are summarised with time. Case-based reasoning (CBR) is used when the operating conditions are varying with time.

The integrated systems can be further expanded with intelligent methodologies, e.g. fuzzy logic, artificial neural networks (ANN) and genetic algorithms (GAs). Various cluster analysis methods are used for finding different situations.

Environmental measurements and open data are processed in the same way as process measurements and laboratory analysis to produce severity criteria (good, usable, still acceptable, not acceptable) for measurements and their trends by nonlinear scaling. Indices obtained from these measurements, which can be continuous or periodic, are utilised in the same way as CM measurements. Adaptation solutions can utilise any available information in process control and decision making (Figure 1) through diagnostics and prognostics (Figure 6).

6 Summary

Integrated smart systems for risk management can be moved towards real-time operation by combining intelligent analysers with the methodologies of risk identification and assessment. Decision support and risk analysis software provide platforms for calculations in special cases. Industrial systems with extensive information require integration with automation systems. In the mining industry, the risk management has two focus areas: (1) water is the main topic in the environmental area, (2) the condition of machines and process devices is important in the mines. The environmental risks are discussed in the risk identification and assessment. The intelligent analysers have been tested in the condition monitoring and integrated with the performance monitoring. The nonlinear scaling can be used for any measurements and open data to develop intelligent indices for the control, maintenance and management.

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