INTELLIGENT BELT CONVEYOR MONITORING & CONTROL: THEORY & APPLICATIONS

Prof.dr.ir. Gabriel Lodewijks[1], Dr.ir. Jaap A. Ottjes[2]
Delft University of Technology, the Netherlands

SUMMARY

At BELTCON 12 in 2003 the concept of strategies for automated maintenance using intelligent monitoring systems was firstly introduced. The main reason to introduce this concept was to optimise the operational performance and reliability of large-scale bulk handling systems. The definition of reliability depends on the aggregation level considered: component, equipment and system. In the concept of applying intelligent monitoring systems to optimise reliability all three levels are important. Over the last two years the concept has further been developed and pilot projects are being carried out in cooperation with the industry worldwide. This paper briefly discusses the concepts of intelligent monitoring systems for the system and equipment level including the application of knowledge-based expert systems. A new approach to build up knowledge in a knowledge-based expert system is introduced. The goal and results of two pilot projects will be discussed and future developments will be sketched. The technical complexities and the operational advantages are highlighted.

1 INTRODUCTION

1.1 Background

Belt conveyors play a critical role in large-scale transport systems as for example used in mining operations. If one of the conveyors in a sequential conveyor system malfunctions then the total system is out of operation. This leads to expensive downtime, especially in terms of cost of lost production. Therefore most mines and power plants continuously monitor their conveyor systems. The purpose of monitoring is to gather information on the systems status in order to assess its reliability. Reliability can be defined as the average percentage of time the system's continuous performance is guaranteed. Belt conveyor reliability can be considerably improved by automating monitoring and maintenance, in particular when looking at the efficiency, accuracy, and costs. Automation of monitoring and maintenance requests intelligent monitoring and control systems.

At BELTCON 12 in 2003 the concept of strategies for automated maintenance using intelligent monitoring systems was firstly introduced [1]. The main reason to introduce this concept was to optimise the operational performance and reliability of large-scale bulk handling systems. It was shown that the only maintenance strategy fit for application in an intelligent monitoring and maintenance system is preventive or predictive maintenance [1]. Operators of large-scale bulk handling facilities try to schedule preventive or predictive maintenance based on the results of visual inspection and signals from installed sensor systems, knowledge of the history of the system, and the operational possibilities for a controlled shut down. The costs of maintenance and uncontrolled shut downs is determined by the combination of the operation of the system and the adapted maintenance strategy. The definition of reliability depends on the aggregation level considered: component, equipment or system. In the concept of applying intelligent monitoring systems to optimise reliability all three levels are important and need to be considered.

Over the last two years the concept of intelligent belt conveyor monitoring has further been developed and pilot projects are being carried out in cooperation with the industry

[1] Gabriel Lodewijks is full professor of Transport Engineering and Logistics in the faculty of Mechanical, Maritime and Materials Engineering of Delft University of Technology, the Netherlands. He is the chairman of the department of Marine and Transport Engineering in the same faculty, and president of Conveyor Experts B.V.

[2] Jaap A. Ottjes is associated professor in the section of Transport Engineering and Logistics in the faculty of Mechanical, Maritime and Materials Engineering of Delft University of Technology, the Netherlands.

worldwide. This paper discusses the concepts of intelligent monitoring systems including the application of knowledge-based expert systems. The sections 2 and 3 discuss the equipment level and the system level respectively. In [2] a Fuzzy Logic based expert system is proposed for the component level. Section 4 finally lists the conclusions and recommendations.

1.2 Information

The information used for belt conveyor monitoring in principle can come from three sources: visually obtained information from human inspectors, information from sensor systems, and information available from enterprise resource planning systems (ERP), see Figure 1. One challenge that is faced when using all three different sources of information is to convert them into one format on which the outcome of the monitoring process can be based.

Specific problems also occur when sensor systems are used to gather information. First of all the right sensors should be used. For example to determine the mechanical torque supplied by a motor to the conveyor system it doesn't suffice to just use the torque reading of a variable speed drive (VSD). In that case the electrical torque instead of the mechanical torque is considered. Therefore wireless strain gauges systems have to be used that are mounted on the shaft of the drive pulleys. When using sensor systems data has to be converted into information. This conversion requests accuracy and domain knowledge. In principle it consists of three steps: data acquisition, data mining, data processing, and data analysis. This has been discussed in [1]. The last step of the procedure will be discussed in Section 2.

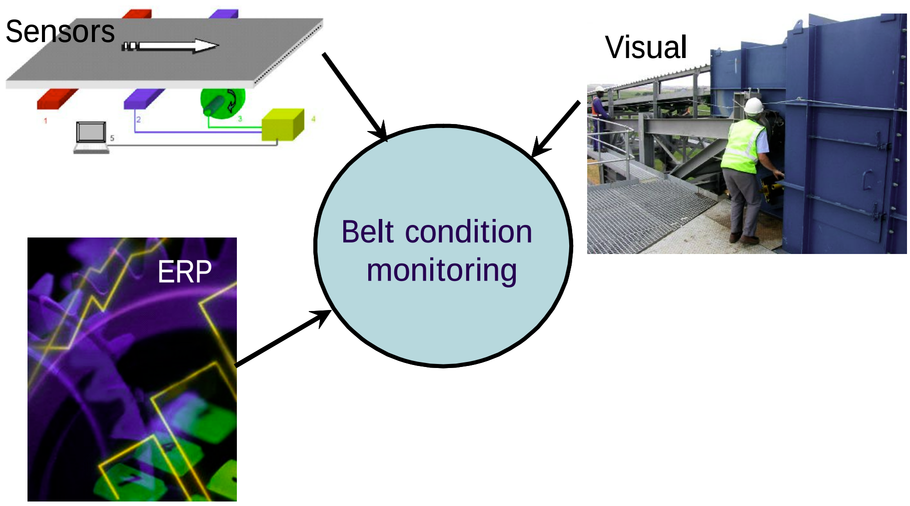

Figure 1: *Three sources of data and information [6].*

Information from ERP systems has its own complexities. First of all it is quite easy to put information into an ERP system, but quite difficult to get it out in the right format. Many ERP systems are set-up as a planning tool and not as a monitoring tool. It is therefore important to decide what kind of information is required for monitoring and in what format it has to be provided when setting-up an ERP system. Secondly, information in ERP systems does not always have the required level of detail. It may for example be known that a specific belt has been replaced and also at what costs, but the reason for replacement may not be documented. It is also possible that certain data is updated once a year and registered per year, which is certainly not the required level of detail for belt conveyor monitoring. This will be discussed in Section 3.

1.3 Intelligent belt conveyor monitoring

Figure 2 shows the process of monitoring a belt conveyor system. A monitoring system is considered intelligent when it can make decisions autonomously on changes in operation or maintenance procedures based on the information discussed in Section 1.2. The process of conveying for which the belt conveyor is used is characterised by bulk solid material and energy getting in and bulk solid material getting out at a different location. In a real belt conveyor the belt conveyor transports a specific material at a certain rate during a period of time. During that process the components wear, damage is generated and existing damage will grow. The *first challenge* is to understand the process of damage generation and growth, as well as general wear development. These are partly determined by the process itself, the material transported, the way the system is loaded etc. In any case the challenge is to detect trends and determine growth models. This will be further discussed in Section 2.

To monitor the wear and damage development of a belt conveyor a monitoring system is required which can get data from three different sources as discussed in Section 1.2. The *second challenge* is to determine the best way to detect and monitor wear and damage in terms of sensor systems, and to combine the information of the three sources so that reliable data in one common format is available. For example: where sensor data can be available on time either in analogue or digital format, the information provided by an inspector is mostly off-line. The latter can be available on-line but that implies that dedicated inspectors are watching the belt conveyor 100% of the time, which is very uncommon in bulk material handling plants.

After data has been acquired it has to be processed into information that can be used to determine the reliability of the system. The reliability of a belt conveyor system can be quantified by using a reliability number, which is an aggregated measure of damage. This number is based on the assessment of the impact of wear and damage on the belt conveyor's performance. One way to perform this assessment, which forms the *third challenge*, is to use an expert system as will be shown in Section 3.

One method that can be applied to determine the reliability of a system is by using the concept of Fuzzy Logic. This subject, which covers also the *fourth challenge*, is further detailed in [2].

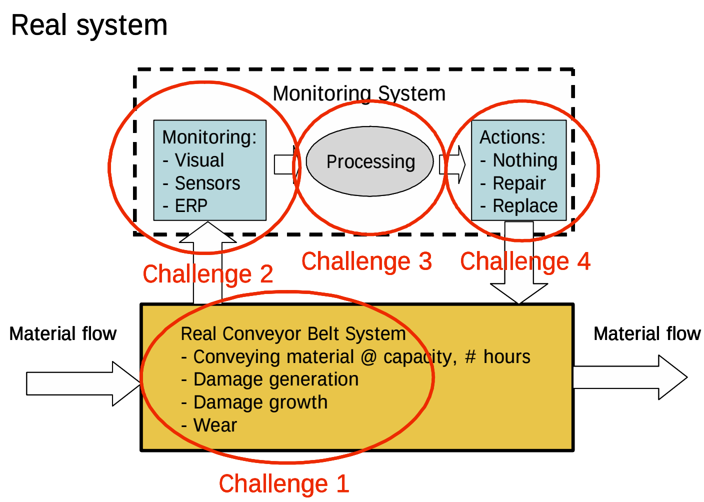

Figure 2: *Overview of the process of monitoring [3].*

Understanding the monitoring process and the ability to use the information it provides enables a feedback to the system so that the reliability target can be met. An important drawback of applying the model shown in Figure 1 in practice is that it takes a long time before the effects of any changes made for example on the maintenance procedures become visible. It is therefore very impractical to test the effectiveness of different maintenance strategies and procedures in practice. For that purpose a simulation model should be used because it enables the analysis of the effectiveness in a very short time [3].

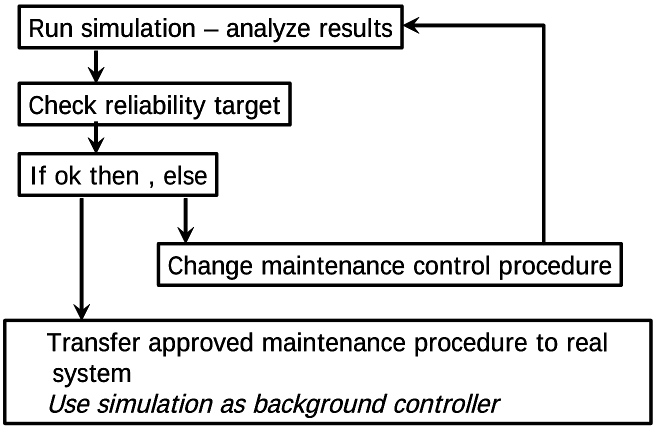

Figure 3: *Simulation as analysis tool and controller [3].*

For simulation purposes the four challenges discussed do not only have to be handled qualitatively, in terms of understanding the process, but also quantitatively, in terms of mathematical models. Logistic simulation models used for the purpose of analysing the effect of different maintenance strategies on the reliability of a bulk material handling facility as developed at Delft University of Technology are based on the process-interaction modelling method [4]. An example of such a model is given in [3]. A general discussion on the use of simulation in the design and control of bulk material handling systems is given in [5]. Finally it should be noted that simulation models are not only used to investigate the effectiveness of maintenance strategies but they are also used as background control to support the monitoring systems in practice, also see Figure 3.

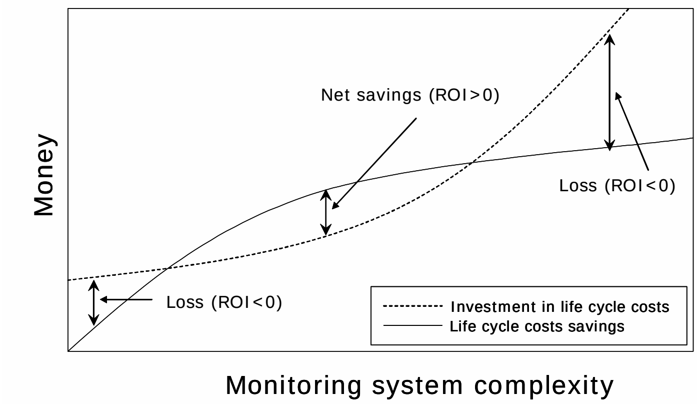

Figure 4: *Costs of monitoring [6].*

1.4 Costs of monitoring

An important source of data and information comes from sensor systems. It is obvious that the amount of information increases with an increasing number of sensors. In addition the accuracy of the information increases with increasing accuracy of the sensors. An increase in number of sensors as well as an increase in sensor accuracy increases the costs of a monitoring system. When implementing an intelligent monitoring system it is important to determine the right level of complexity of the system. Figure 4 qualitatively shows the investment costs (dotted line) and the cost savings (solid line) of a monitoring system as a function of its complexity. Cost savings are the result of an increase in reliability of a belt conveyor system. As can be seen in Figure 4 the initial cost of a monitoring system, associated with the processing unit, interfaces and a minimum number of sensors, will exceed the cost savings. When sensors are added or more accurate sensors are used the complexity of the monitoring system and thus the investment costs increase. The cost savings however will increase more. At a certain level of complexity the cost savings exceed the investment costs and a net saving is achieved. In that case the return on investment (ROI) is positive. When the complexity is further increased there is a level where the costs to further increase the accuracy of the monitoring system are disproportional and the return on investment again becomes negative. The challenge is therefore to determine the optimal complexity of an intelligent monitoring system in terms of return on investment.

2 EQUIPMENT LEVEL: THE BELT CONVEYOR

The application of fuzzy sets and the logistic control of conveyor belt maintenance as discussed in [2] only concerned the conveyor belt, which is one component of the total system. If a total belt conveyor is considered as a technical system then the question raises how the performance of individual components affects the reliability of the total system. Instead of monitoring one component, all major components need to be monitored and the combination of information on the technical status of components needs to be translated into information of the total system. For that purpose knowledge based expert systems can be used.

An overview of a knowledge-based expert system is shown in Figure 5. A good overview of the details of the application of a knowledge-based expert system in belt conveyor monitoring is given in [7]. A knowledge-based expert system (KBES) uses two procedures: a case-based reasoning case retrieval procedure, which consists of two steps, and the knowledge-based case adaptation procedure that consists of one step.

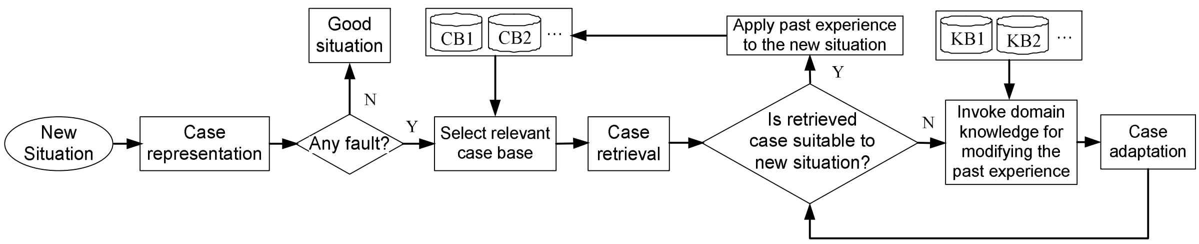

Figure 5: *Overview of a knowledge-based expert system for belt conveyor monitoring.*

2.1 Case retrieval procedure

In the terminology of knowledge-based expert systems the current state of a belt conveyor is called the new situation. For the new situation the belt conveyor monitoring systems gathered data from for example the sensors in the conveyor system. This data represents the value of key parameters that are called events, S_e.

The case-based reasoning (CBR) case retrieval procedure carries out case matching and retrieving by similarity evaluation and hierarchical indexing organization [7]. The retrieval procedure consists of two steps: case representation, which is made up by event identification, event quantification and event representation, and case retrieval.

2.1.1 Case representation

Event identification

The arriving new situation has a set of events S_e that indicate the real condition of the system's performance. Event identification embodies an event behaviour pattern. During a certain period event i has behaviour j that belongs to behaviour category C_e. The event "belt speed”, for example, can exhibit the following behaviours: slow or fast increasing, slow or fast decreasing, constant.

Event quantification

Event quantification evaluates whether the variance is outside the normal range or not, and denotes the probability that an event leads to system or component failure, also called a fault. A fault can be quantified by probabilistic analysis. For example, the probability that the event “belt speed” will deviate from normal levels is P_n(belt speed):

$$P_n(\text{belt speed}) = \frac{\text{desired belt speed} - \text{actual belt speed}}{\text{desired belt speed}} \tag{1}$$

Event representation

A monitored operational situation can be represented as follows:

$$MS_n = \{MS_n(i.j) | i \in S_e, j \in C_e\} \tag{2}$$

where n is the n^{th} monitored situation.

2.1.2 Case retrieval

Past cases consist of representations, discoveries and successful experiences and are classified into case bases (CB). When a new situation arrives with any fault, the past cases are scored by similarity evaluation in order to retrieve the most similar case to the new one. If a past case with high enough similarity is found, past experiences can directly be used. To evaluate the similarity between a past case and the new case, match factors are used. A match factor MF denotes the closeness between the event identities of a past monitored situation $MS_p(i,j)$ and the n^{th} new monitored situation $MS_n(i,j)$. The match factor MF is defined as:

$$MF = MF_i(MS_p(i,j), MS_n(i,j)) \tag{3}$$

Consequently the similarity between the past case C_p and the new case C_n is defined as:

$$S(C_p, C_n) = \frac{\sum_i P_n(i) MF_i(MS_p(i,j), MS_n(i.j))}{\sum_i P_n(i)} \tag{4}$$

The fault probability $P_n(i)$ is the probability that the event n leads to system or component failure, as defined in equation (1). In equation (4) the summation index is parameter i (event) but not j (pattern of behaviour) because there is a set of events in any case but one event has only one behaviour pattern during certain monitoring period. Therefore, obviously, only events that have the same behaviour j are match able. See reference [7] for more information.

2.2 Case adaptation procedure

If no past case with high enough similarity is found then the retrieved past case needs to be adapted. A low similarity means that there is a gap between the most similar retrieved past case and the new case. When this happens and no past case with higher similarity can be found, the knowledge-based adaptation procedure is triggered to detect and reconcile the discrepancies. The case adaptation procedure includes two heuristic adaptation methodologies – statistical heuristics and rule-based reasoning.

When the event identification procedure cannot deal with the dissimilarity between two cases, statistical heuristics will be applied for reducing or eliminating the deviation. Statistical procedures that are available for this purpose include trending analysis, correlation analysis, cluster analysis, regression modelling, and causal modelling.

Sometimes a very special situation arrives and there is no complete knowledge base known for reconcilement. In that case the adaptation procedure is implemented by rule-based reasoning. Heuristic rules, which have been collected from domain specialists, consist of key properties of diverse nature to limit the application domain of the rule. These key properties include for example belt categories, mechanical properties, special operational strategies, and so on. When the situation or events in the ***if*** part of a rule are matched, then the rule provides an operational decision for adaptation.

2.3 Building a knowledge base

A knowledge based expert system only works well if sufficient knowledge is available in the system to cover the range of situations monitored. The strength of a KBES is that it gives a straightforward advice once a situation is retrieved from the database similar to the monitored situation. The proper course of action used in the past can then also be used in the current situation. However, when a KBES is installed there hardly are any past situations. In that case an expert has to invest a considerable amount of time into identifying monitored situations, determining whether or not this situation is faulty or not, and if it is faulty how to reconcile the situation into an acceptable situation. It is important here to consider the application of fuzzy sets to limit the number of possible situations that can be monitored.

To investigate whether or not a knowledge base can be build up before the KBES is installed on a belt conveyor system a research project is carried out in cooperation with Svendborg Brakes A/S. In this project the focus is on a sub-KBES, which works as a software agent in a bigger KBES, that monitors the performance of a brake used on a belt conveyor (also see Figure 6). The main research question of the project is whether or not simulation can be used as a tool to build up a knowledge base.

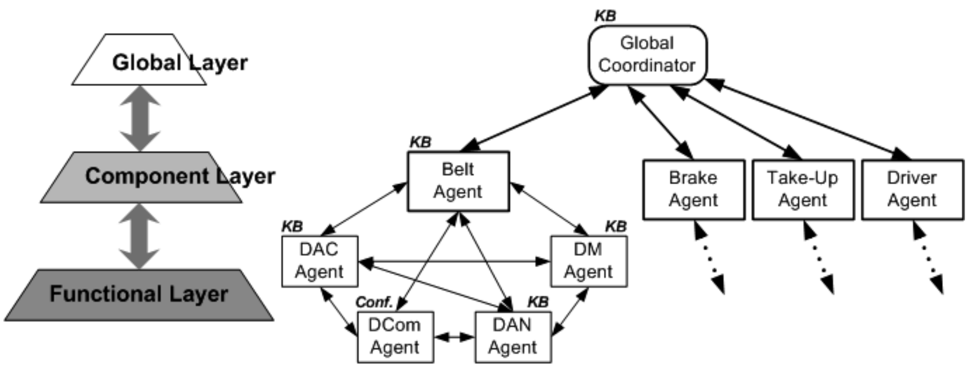

Figure 6: *Hybrid architecture of a multi-agent KBES.*

A dynamic model has been made of a brake, including both the mechanical and the hydraulic components. The parameters of this model include parameters of the real brake of which the values can be determined in practice by using sensors. With this model numerous calculations have been made all analyzing different “what if” scenario’s. Examples of what if scenarios are:

- What happens if the hydraulic line is broken?
- What happens if the back-pressure valve malfunctions?
- What happens if a power outage occurs?
- What happens if the brake controller fails?

With the model the "what if" scenarios have been simulated and the change in values of the model parameters have been determined. This change in parameter values determines the change in the situation of the brake. This change in situation represents the new situation as can be determined in practice by a KBES. For all "what if" scenarios the virtually monitored situations have been determined and a proper course of action is attached to this situation by a brake expert. Herewith a database is build up with relevant cases and matching actions. To answer the main research question of the project experimental validation is required of the usability of the knowledge base, which is build by using simulation as a tool. Experimental validation will be carried out in the Svendborg laboratory in Vejstrup, Denmark.

3 SYSTEM LEVEL: A MINING OPERATION

The previous paragraph discussed belt conveyor monitoring on component and equipment level. Over the last two years the section of Transport Engineering and Logistics of Delft University of Technology worked together with the belt conveyor department of RWE Rheinbraun, Germany, on a project to investigate the application of intelligent monitoring and control of maintenance activities on system level. Questions that triggered this project were:

- What is the chance that we will experience a major shutdown before the next scheduled stop?
- Previously we changed out belting after 6 years. Today we do so after nine years. What is the optimum?
- If we change our maintenance philosophy, how can we determine the effect of this change in advance?
- A belt conveyor system consists of many components. How can we distinguish the influence of one component on the system's reliability from the other?

To answer these questions a proper logistic model is required that can be used to analyze the effect of different maintenance strategies and monitoring systems on the overall systems reliability, also see [8] & [9]. This logistic model, which is under development, is based on detailed models of the systems components as for example discussed in [2], and the monitoring tools as discussed in paragraph 2.

An approach has further been proposed including:

- Combine human inspection data and sensors data in an automated maintenance system.
- Collect and record on line data with respect to belt load and damages behaviour obtained from sensor measurements and visual inspections.
- Convert recorded data into statistics to be used for improving predictions about damage behaviour as a function of time.
- Use on line measurements for improving quality of damage prediction thus saving on operational costs

A model structure is presented in Figure 6 to evaluate possible gains of the approach. The modelling project will be continued and parallel to that a worldwide project is started in cooperation with industrial partners to collect industrial data for use as data to prepare proper model input.

4 CONCLUSIONS

At BELTCON 12 in 2003 the concept of strategies for automated maintenance using intelligent monitoring systems was firstly introduced. That paper introduced the concept of using simulation as a tool to analyse the effect of different maintenance strategies. It was concluded that the performance level of intelligent maintenance procedures depends on the accuracy of the estimation of the remaining lifetime of components. The accuracy of this estimation depends on the availability of a model predicting the deterioration of a component. With such a model, fed by information from sensors used in a monitoring system, the remaining lifetime can be estimated well. The information used in monitoring systems as well as the concept of intelligent belt conveyor monitoring and its challenges were discussed in Section 1 of this paper.

With the technical state of components being known section 2 showed a technology that can be used to access the technical state of the total belt conveyor system. Usage of Knowledge Based Expert Systems enables operators to automatically monitor a conveyor system and to receive straightforward advices on how to reconcile faults, if applicable.

In Section 3 an approach for the analysis of the effect of different maintenance strategies on the overall system's reliability was introduced. This approach can also be used for the logistic control of the actual maintenance activities.

Finally, one challenge for the future is to design belt conveyor systems and their controls in such a way that the technology as presented in this paper can be build-in from the design stage. This requires commitment of manufacturers of components and systems as well as a thorough understanding of the physical phenomena that occur in belt conveying. However, despite the technical challenges the significant advantages for operators and companies that lease out their equipment make up for the required efforts.

5 REFERENCES

[1] Lodewijks, G. (2003), "Strategies for Automated Maintenance of Belt Conveyor Systems", proceedings of the BeltCon 12 conference, June 23-24, 2003, Johannesburg, South Africa.

[2] Lodewijks, G. and Ottjes, J.A. (2005), "Application of Fuzzy Logic in Belt Conveyor Monitoring and Control", proceedings of the BeltCon 13 conference, August 2-3, 2005, Johannesburg, South Africa.

[3] Lodewijks, G. and Ottjes, J.A. (2004), "Optimization of Maintenance Strategies for Large Scale Transport Systems", *Proceedings of the 8th International Conference on Bulk Materials Storage, Handling & Transportation*, 5-8 July, Wollongong, Australia, pp 299-304, ISBN 085825-795-5.

[4] Zeigler, B.P., Praehofer H and Kim T.G., (2000), *Theory of Modelling and Simulation, 2nd Edition*, Academic Press, San Diego.

[5] Lodewijks, G. and Ottjes, J.A. (2004), "Reliability of Large Scale Bulk Material Handling Systems", *Bulk Solids & Powder Science & Technology* ***1***, pp. 9-17, ISSN 1613-4370.

[6] Lodewijks, G. and Veeke, H.P.M. (2004), "Automation of Transport & Production Systems", lecture notes of Course Wb3421-03, Delft University of Technology, Delft, the Netherlands.

[7] Lodewijks, G. and Pang, Y. (2004), "A Knowledge-based Expert System for Intelligent Conveyor Belt Monitoring", *Proceedings of the 8th International Conference on Bulk Materials Storage, Handling & Transportation*, 5-8 July, Wollongong, Australia, pp 317-321, ISBN 085825-795-5.

[8] Wallien, K.H. (2002), "Onderhoudsstrategie van een onderhoudsrobot voor bandtransporteurs", Report number 2002.LT.5602, Delft University of Technology, the Netherlands.

[9] Koenis, R.E.M. (2002), "Simulatie onderhoudsrobot voor een bandtransporteur", Report number 2002.LT.5668, Delft University of Technology, the Netherlands.