Abstract – The development of knowledge-based systems (KBS) enables accumulated experience and knowledge to be applied to the intelligent monitoring in the field of large-scale belt conveyor systems. The first step of building knowledge bases in a KBS is referred to the knowledge acquisition (KA). KA from domain experts and field experiments has often been considered as the most difficult task and time-consuming process. This paper introduces a methodology for knowledge-based intelligent belt conveyor monitoring that uses simulation to speed up and simplify the process of KA. Results of laboratory experiments show the efficiency and the accuracy of the introduced simulation-based KA method.

1. INTRODUCTION

Belt Conveyor Systems (BCS) have been significantly developed for decades in large-scale continuous transport systems. Nowadays critical components of most large-scale BCS are monitored in real time. Since the early 1980’s, conveyor belt monitoring (CBM) has become an established tool for BCS maintenance programming and the determination of control strategies [1]. Traditional CBM systems tend to carry out in response to catastrophic failure and generally include one or several alarms that go off when a working point is exceeded or when a trend deviates from the expected value in time.

Maintenance of BCS can be divided into condition monitoring of the whole system and servicing of its components. Instead of the term of CBM, the term of belt conveyor monitoring (BCM) implies that a modern monitoring system concerns BCS as a whole but not only the belt itself. To overcome operational problems caused by the lack of domain knowledge of inspectors BCM can be automated. However, intelligent BCM (IBCM) is still in early stage. In order to optimize maintenance efforts and improve the operational performance and reliability of BCS, the concept of applying strategies for automated maintenance by using intelligent monitoring systems was firstly introduce on BeltCon 12 [2]. Furthermore, in 2004, a knowledge-based expert system (KBES) for IBCM had been proposed [3]. The KBES effectively stores and applies the successful operational experience and expertise of domain specialist for improving the performance of BCS.

However, knowledge acquisition (KA) is a bottleneck of developing knowledge-based systems (KBS) [4] especially in the field of large-scale BCS. When the knowledge has to be built up with data from domain specialists and BCS operating in the field, it will probably take several years before sufficient knowledge is collected. Even then the question remains whether or not the built-up knowledge covers all possibly occurring situations.
This paper presents a simulation-based KA method that builds up knowledge bases (KBs) for implementing a KBES for IBCM. This method is independent of when specific operational situations occur on the real system. The operational situation can be set in a model and then the simulation can be run. After the generated information is represented as knowledge and stored in KBs, it can be retrieved and used by the intelligent reasoning process of the KBES.

In this paper, section 2 gives a brief view the KBES for IBCM. Section 3 summarizes the main principles of modeling and simulation. After introducing the algorithms of knowledge representation and reasoning process for decision making in section 4, laboratory results in section 5 show the efficiency and the accuracy of the introduced simulation-based KA process. This paper is finished by some conclusions in section 6.

2. INTELLIGENT BELT CONVEYOR MONITORING

Over the last decades, KBS have been introduced in many segments of industry but not come into use for large-scale BCS. It is caused by the fact that each BCS has its own specific operating situations that make applications of condition monitoring difficult. In general, maintenance on BCS can be divided in inspection or condition monitoring of the total system and replacement and reparation of its components. Nowadays more and more companies outsource maintenance in an attempt to balance the budget and reduce the number of permanent staff members. Therefore, a demand has risen from the belt conveyor industry for intelligent systems that are able to monitor BCS and decide on maintenance.

As mentioned in [2], there are four typical types of BCS maintenance: preventive maintenance, random maintenance, corrective maintenance and predictive maintenance. It is clear that only a predictive maintenance concept qualifies for application in an intelligent maintenance system that enables maintenance automation. Therefore an IBCM system is the premise of automated maintenance. In 2004 a KBES for IBCM had been introduced which replaces efforts in information interpretation, system assessment and operational decision-making (Figure 1).

![Fig. 1: Knowledge-based expert system for intelligent belt conveyor systems.](image)

This system applies a case-based reasoning (CBR) procedure that provides similarity evaluation for accurate case completion and a hierarchical case indexing for retrieving the most relevant case efficiently. When the currently monitored situation deviates from the most similar case retrieved, the adaptation procedure uses accumulated domain knowledge to reconcile the discrepancy.

3. KNOWLEDGE ACQUISITION

Before a KBES can be built-up, knowledge about the operational situation of BCS should be gathered. Three methods exist for gathering the required information. First of all one could collect data of the situations monitored together with their accompanying operational situation from a BCS operating in the field; the second approach is to collect operational experience by inquiring domain specialists; and the third is to collect the knowledge from a software simulation model that generates all situations that could possibly be monitored.
The acquisition and the elicitation of knowledge from field experiments and domain experts have often been considered as the most difficult and time-consuming task in KBS development [4]. Especially in the BCS field, the KB of supporting an IBCM originates from various techniques and various sources other than human experts. The main advantage of the third method over the others is that the development time of the KBES is significantly shortened. The simulation-based method is independent from specific operational occurrences on the real system. The operational situations can be set in a model and then be simulated by using a software model. The model should be possible to gather enough knowledge of BCS system and its components that can be used as input for a KBES.

3.1 Principles of modeling

The model is used to simulate the system and generate knowledge for decision-making in specified operational situations. Such a software model should be able to simulate both healthy operational situations and failure modes. The objectives for the development of the model are:

- To gather knowledge about system behaviors during normal operational situations.
- To gather knowledge about system behaviors after introducing operational failures.
- To store the gathered knowledge in KBs that can be used by the KBES to determine the occurring failures in the system.
- To simulate the real system accurately enough.

To reach these objectives, the model should firstly meet the following overall requirements:

- Qualitatively correct description of system behaviors during normal operation and operation after introducing failures.
- Quantitatively correct description of system behaviors during both normal operation and operation after introducing failures.

Secondly the structure of the model should meet the following requirements:

- the model should be based on process physics to enable correct introduction of failures.
- The model should contain sufficient adjustable parameters to enable model matching.
- The model should supply measurable variables that are comparable with measured data.
- The model should be modular to contribute to the maintainability and comprehensibility.

3.2 Verification, Matching and Validation of model

The verification, matching and validation of model should base on the process shown in Figure 2.

![Diagram: Process of verification, matching and validation of model]

- **Verification**
  - Define Model
  - Initialize states → Stabilize simulation → Establish results
  - Determine Parameters → Steady matching → Dynamic matching
- **Matching**
  - Accurateness → Stability
- **Validation**
  - Valid Model

*Fig. 2: Process of verification, matching and validation of model.*

*Verification* initially evaluates the model and shows the ability of the model of representing the physical process based on theoretical process knowledge. Verification contains three steps. The first step defines the initial situations of resulting in a converging set of equations for the model and identifies and solves errors that deter the model from stable simulation. The second step enables the
model numerically stable enough to run the largest time constant to make evaluation of the results possible. The third step assesses the results following expected trends and ranges.

Matching is the adjustment of parameters in the model, such that the simulated outputs approximate the measured data as accurately as possible over the entire operational range.

Validation compares the measured data with the simulated data and calculates an error by taking for example the quadrate of the difference for each set of measured and simulated process value.

4. KNOWLEDGE REPRESENTATION

An algorithm of fuzzy knowledge representation has been developed to represent both simulated data and monitored data. Represented simulation data is considered as past operational situation stored into KBs as the input of the case retrieval in the KBES. Represented monitoring data is considered as new operational situation updated timely and used as the input of the reasoning procedure of the KBES. The final maintenance decision for newly monitored operational situation is carried out by a case completion procedure.

4.1 Knowledge Representation from Static Information

Data generated from simulation is located in a specific database as static information. An observation window is created to collect data within a certain time period, the window length, to represent static information by the fuzzy knowledge representation algorithm. Each batch of data collected by observation window is represented and stored into KBs as past cases.

![Fig. 3: Observation window (short interval).](image3.png)

![Fig. 4: Observation window (long interval).](image4.png)

The length of observation window “l” and the sample interval are changeable with the premise of gaining sufficient information. Figure 3 and Figure 4 show the cases of short and long sample intervals which are suitable to observe fast varying events and slow varying events, respectively.

4.2 Knowledge Representation from Dynamic Information

To dynamically collect data from monitored field within a certain time period, a data flow tunnel is set. The data tunnel samples data passing through the tunnel with defined tunnel length “l” and represents the currently monitored situation as new cases.

Tunnel length “l” and sample frequency are also changeable depending upon different monitored system components and parameters. High sample frequency (Figure 5) is suitable to fast variant events such as parameters of emergency braking system. Some slowly varying components such as belt itself, the corrosion, the misalignment, etc., low sample frequency is sufficient (Figure 6).
4.3 Case completion and decision making

The case completion algorithm completes partial and incomplete information into a recognizable operational situation stored in KBs. It is applied by evaluating the similarity between new and past operational situations and then to retrieve the lacked knowledge of incomplete cases such as operational discoveries and maintenance solutions exist in past complete case (Figure 7).

Fig. 7: Case completion and decision-making.

5. IMPLEMENTATION

Principles of the simulation-based KA process are shown in Figure 8. Data and information from simulated situations are represented and stored in case base and to be retrieved by the CBR procedure. When a newly monitored situation arrives, relevant information and data are firstly represented and considered as the input of the CBR. Case completion carries out the decision-making of maintenance strategies and operational suggestions.

Fig. 8: Process of simulation-based knowledge acquisition.

A test facility of hydraulic brake system of BCS (Figure 9) had been applied for evaluating the model, the simulation-based KA approach and the IBCM.

The analyzed brake system consists of a hydraulic disc brake, a belonging hydraulic power unit and a controller. The controller monitors the speed of the brake disc and depending on this speed, it controls the amount of oil the hydraulic power unit supplies to the brake. This delivered amount of oil determines the braking force with which the brake is applied to the brake disc and as a result the deceleration of the brake disc.

The KBES gives output with the \textit{Scode} of newly monitored situation, the \textit{Scode} of retrieved situation, the indication of possible system failure mode and relative operation solution, and the confidence level of case retrieval (Figure 10). The \textit{Scode} is the simplified process situation representation. Indication of retrieved decision-making solution originally comes from its simulation initial setting.
The simulation-based KBES had been tested by effects of failure modes in the hydraulic brake system on the behaviors of both the simulated and measured process values. The KBES can be evaluated based on the output it gives. During field tests, the operational situation of the measured data offered to the KBES is known, which means that the failure mode is known. Therefore, it is easy to verify if the retrieved process discovery and decision-making solution given as output by the KBES corresponds with the failure mode as measured. Figure 11 shows the evaluation results of the KBES during the blocks of ten seconds braking time, offering the measurement during failure mode of “control pressure low”.

6. CONCLUSIONS

Knowledge systems and intelligent monitoring technologies are gradually playing a major role in the modern BCS. One unique aspect of the introduced simulation-based method is that the solution of the bottleneck problem of KA during developing a KBES is achieved by the use of software model in discovering operational solution and maintenance strategies in BCS performance. The simulation-based method shortens and simplifies the KA process and shows its efficiency and accuracy of building up KBs for an IBCM. From experimental results it can be concluded that the simulation-based IBCM provides correct enough maintenance decisions.
7. REFERENCES


