A Bayesian Belief Network Approach to Belt Conveyor System Monitoring

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Abstract: To optimize belt conveyor system (BCS) performance, a reasonable assessment of system reliability is desired and the decisions of how often to perform maintenance and the optimal occasion to replace a component are required. Intelligent belt conveyor monitoring (BCM) may automate the maintenance process. To realize such an intelligent system most of parameters of BCS have to be monitored. Too many monitored parameters during operation phases cause system complexity. This paper presents a Bayesian Belief Network (BBN) approach to BCM to predict failures, discover component fault causes, evaluate the system reliability and decide on maintenance strategies. The BBN model encodes probabilistic dependencies among monitored working variables into a directed acyclic graph of Bayesian causal structure. Reasoning of such a BBN results in alarms of abnormality of monitored variables, maintenance and replacement decisions for degraded components, optimal operational strategies of system functioning and evaluation of system condition.

1 Introduction

Traditional large-scale belt conveyor systems (BCS) are inspected visually by domain specialists in belt conveyor monitoring (BCM) to determine the general operational condition. Today critical components of BCS can be monitored in real time. As a complex industry process, failures of equipments and the abnormality in system operations are usually detected by sensors in BCS. The operators or inspectors have to isolate failure causes by analyzing sensor signals. The time until the failure source is discovered and the subsequently resulted unplanned system interruption are the main causes of BCS downtime. To get a good impression of the operational status of a BCS more information is required and has to be reasonably analyzed. However, the large amount data and monitored variables and the parameters subject to a great deal of uncertainty cause system complexity.

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and make failure analysis difficulties more. These problems will not be solved by even the most experienced domain specialists.

To overcome operational problems caused by the lack of experience of inspectors BCM can be automated. To monitor BCS in an intelligent way with less or no human efforts is desired. Currently BCM takes into account expert knowledge, system degradation and feedback observation in order:

- to assess equipment lifetime and quantify component degradation or system failure possibility;
- to monitor important variables related to system degradation and decide maintenance tasks;
- to quantify the effect of maintenance actions on system operations;
- to provide system diagnosis and decision making;

In reality, the continuity of BCS performance requires high level automation of operation and maintenance control and suggestions to human operators on corrective operational actions. Regarding to the functions of a fault diagnosis system for BCS operations, a BCM system should satisfy the requirements of early detection and diagnosis, isolability, robustness, multiple fault identifiability, explainability, facility, adaptability, storability and computability. The methodology of Bayesian inference is a sound tool to reach these requirements. Compared with other methodologies, if only a classification of failure types is required, neural networks or statistical classifiers may be adequate. However, if decision support is needed in an intelligent system these methodologies would not provide causal interpretation of diagnostic conclusions [1]. After 2000, Leung presented a probabilistic approach to fault diagnostics in combination with multivariate data analysis [2][3]. In addition, Arroyo developed dynamic Bayesian belief network (BBN) for diagnosing and predicting failures in industrial plants [4]. Previous works showed that Bayesian methodology for probabilistic reasoning calculates the posterior probabilities which provides the insight of relationships in industrial systems.

This paper presents a probabilistic modeling approach to intelligent BCM by using BBN. In this study, a BBN describes a causal representation of the phenomena involved in BCS degradation. The BBN model consists of four layers: the environment layer, the degradation layer, the observation layer, and the system layer. The model is used to characterize uncertainties in BSC process, assess and optimize system reliability, decide how often to perform maintenance and the optimal occasion to replace a component. The BBN approach can be used to support operators and decision makers in BCS performance and the formulation of operational policies. In this paper, Section 2 briefly introduces the principles of BBN approach. Section 3 presents the methodology of BBN modeling. The results of BBN implementation are shown in Section 4. Finally conclusions of this study are given.

2 Bayesian Belief Network and Modeling

BBN is a formalism for reasoning under uncertainty [5]. It has become an effective approach to model various expert systems such like medical diagnosis, troubleshooting, image interpretation and so on. In
industry, BBN provides an efficient way to represent the degradation of system, machine, equipment or component. Therefore it could be considered as useful to help engineers to fulfill BCS maintenance.

The foundation of the BBN is the Bayes theorem which can be described as for any events $A$ and $B$,

$$P(B \mid A) = \frac{P(A \mid B)P(B)}{P(A)}$$

denotes the conditional probability that $B$ occurs, given that $A$ is known to occur. In BCM process, if $B$ refers to a continuous variable and $A$ represents the new observed data, then $P(B)$ is the prior probability that $B$ occurs; $P(B \mid A)$ is the posterior probability of $B$ occurs, given $A$; and $P(A \mid B)$ is the conditional probability that $A$ occurs, given $B$. This formula enables us to use the prior knowledge of an event to calculate the probability of the other event(s).

In detail, a BBN is an acyclic directed graph that represents a factorization of the joint probability over a set of random variables. The graphical structure of the network is the qualitative part of a BBN and embodies a set of nodes representing the random variables and a set or arrows representing direct dependencies between connected variables. Absence of an arrow between variables indicates that these variables are conditionally independent. The parents of a variable are the variables connected with an arrow with its direction going into this variable. The joint probability is the quantitative part of a BBN and embodies the conditional probability defined with each variable. This probability characterizes the influence of the valued parents on the probabilistic values of the variable itself. A probability is the prior probability when a variable has no parents. The uncertainties in the parent nodes, represented by marginal probability, produce uncertainties in the child nodes that are based on conditional probabilities and physical cause-and-effect relationship. The directed graphs of BBN provides a representation of the set of variables that are related to each other in providing knowledge about the state of the system [6]. BBN is particularly useful for communicating risk and uncertainty and providing a framework for analyzing complicated cause-and-effect relationship in a simple and readable way. BBN can be also regarded as a way of introducing randomness in influence diagrams. Two recent studies of such maintenance modeling methodology are influence diagram [7][8]. Another example is the conveyor belt maintenance decision-making by using fuzzy Bayesian modeling [9].

### 3 Modeling Methodology

The data used to model a BBN includes historical records of system performance, observed information, expert judgment, and surveyed opinions. To build a BBN in BCS field, information from these sources are used to define relationship among variables. Modeling knowledge can be derived from frequency data or elicited from an expert judgment. However, nowadays the development of intelligent BCM is still in early stage and normally no sufficient data is available in most of BCS fields. Therefore in practice we firstly address problems of deriving reliable information from domain
specialists in a graphical model setting and then propose a method to obtain honest probability values in a simple and interactive way from expert knowledge. Also statisticians play a role of mediator to clearly define the goal of modeling and describe various possibilities of building such a model.

In modeling process, quantitative relationship and qualitative relationship among variables are defined. The first consists mainly of if – then statements. For example, if the BCS overload is, then the belt tension is high, or, if the belt tension is high, then the BCS overload might be. The second represents the whole system based on the physics of BCS and the economics of BCS performance.

The main goal of this study is to model system degradation with a BBN in order to assess risks, predict failures, define appropriate maintenance actions and evaluate possible effects of maintenance actions. To achieve these objectives, the BBN model is structured to represent key variables, management alternatives, and cause-effect relationships in a clear and intuitive way. In principle, a designed model consists of four layers (Fig.1). The environment layer includes BCS key variables which monitored directly by sensors; the degradation layer is composed of variables represent the healthy conditions of components by means of degradation probabilities; variables in the observation layer represent the functioning performance of BCS; and the system layer evaluates the situation of the whole system.

Bayes rules can be used to discover potential changes of child variables when parent nodes vary. This is the “forward reasoning” of BBN. Bayes rules can also be used to discover the probabilities of the changes of parent variables based on known valued evidence of a child node or the information about the probability of a child node variance. This is called the “backward reasoning”. So different goals can be set at end nodes and then BBN reasoning defines policies to achieve these goals. For any identified abnormal situation, the BBN discovers the causes of observed or predicted problems. The basic algorithm of discovering and searching the causes follows steps:

- to acquire on-line evidence from sensory signals, data trends, effects, etc.;
to represent evidence into states;
• to assess the risk of the abnormality of each variable;
• to present the risk assessments and the measurements of physical variables and observations;
• to evoke inference engine for automated reasoning and probability update;
• to compute the probabilities for all possible causes of problems;
• to provide discoveries and advices on maintenance or control activities;
• to select the expected efficient actions;
• to adapt and update reasoning knowledge based on observation after performing actions;
• to collect operator feedback on the real causes of problems;
• to update BBN and prove it with new indicated situations.

This procedure continues in loop until the problem is solved or the best actions are suggested.

4 Implementation

The above described methodology has been applied for building a BBN in BCM. An application has been developed in Delphi environment to realize the model. Presently main goals of the application are to model BCS performance to discover system abnormalities, evaluate component degradation and define the most appropriate maintenance actions. This application is able to handle 112 environment variables, 16 component variables, 4 observation variables and 1 system variable.

Fig. 2: Implementation of a Bayesian belief network

Fig. 3: Risk analysis of the Bayesian belief network approach

Fig. 2 presents a BBN contains 13, 4, 3 and 1 variables in its four layers. Measurements are real continuous data shown in each environment node where the probability of the abnormality of each
parameter is not shown in the interface. Values of probabilities of components degradation, system functioning assessment, and system situation evaluation are shown in their own layers respectively. Implementation results encourage adding maintenance tasks on the component of brake which appeared strongly influencing the system and further paying more attentions to the system functioning of stopping belt which has higher failure probability. These results are also intuitively shown in Fig. 3.

The cause(s) of component degradation and (potential) system failure can be discovered by the backward reasoning of BBN. In the case shown in Fig. 2, a worse belt stopping functioning was caused by the considerable degradation on brake, and the brake degradation may be caused by abrasion of brake pad, abrasion of brake disc, insufficient braking torque, or lower take-up tension. Based on the initial setting of monitored parameters and the posterior probabilities of the brake degradation, the real and main causes of system degradation can be discovered and meanwhile the relative operational actions can be suggested.

5 Conclusions

BBN approach has been approved as a powerful tool to model the relationships and associations among relevant variables in other application fields. A BBN application was developed to quantify uncertainties in the operations of BCS performance. Results of implementing the BBN application showed the abilities of Bayesian inference on aspects of fault diagnosis, failure prediction, discovery of cause-and-effect relationship, and reduction of uncertainties in BCM process. Current application focuses on proving the feasibility of using Bayesian inference to the intelligent BCM system. To reach a mature BBN, more key variables should be monitored and concerned into the model and the model needs to be improved.

References: