Strategies for Automated Maintenance of Belt Conveyor Systems

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Summary

This paper discusses automation of maintenance of belt conveyor systems, in particular of idler rolls. Automation of maintenance is a promising alternative for outsourcing maintenance, in particular when looking at the efficiency, accuracy, and costs. In order to optimise maintenance efforts, the concept of intelligent maintenance is introduced. The powered maintenance trolley that can travel autonomously over the structure of a belt conveyor is adapted as a platform of the maintenance system. On this trolley, data acquisition equipment for vibration analysis is installed. Data mining can be done either on board of the trolley or in a central computer depending on the maintenance strategy. The optimum maintenance strategy is determined by a logistic simulation model that accounts for the lay-out of the belt conveyor itself and the accuracy of the information on the remaining lifetime of its components.

1 Introduction

Today more and more companies outsource maintenance in an attempt to balance the budget and reduce the number of permanent staff members. Outsourcing maintenance however only works if the company that takes over maintenance employs well-trained and experienced personnel that stays on a specific job for a considerable time. Unfortunately, reality is different and many companies have poor experiences with external companies performing maintenance.

In general, maintenance on belt conveyor systems can be divided into inspection or condition monitoring of the total system and replacement and/or reparation (in short servicing) of its components. Most problems experienced with outsourcement of maintenance are associated with the inspection or condition monitoring of a system. It is not trivial to access the status of sometimes moving components of a belt conveyor. The same experienced person should therefore carry out inspections on a regular basis.

To overcome operational problems caused by a lack of experience of external maintenance personnel, the inspection of belt conveyor components can be automated. In this way knowledge of for example wear rates and replacement schedules can be built up in a data base system. The external maintenance crew then can be used to replace the worn off

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components. Alternatively, replacement of components can be automated as well.

This paper discusses strategies and techniques for automated maintenance of belt conveyor systems. Section 2 defines the concept of intelligent maintenance, Section 3 discusses existing inspection systems that can be used in automated maintenance systems. Section 4 discusses means of assessing the status of rotating components of belt conveyors based on vibration based monitoring concepts. Section 5 presents a case study and section 6 finally lists the conclusions and recommendations.

2 Intelligent maintenance

Maintenance on belt conveyor systems can be divided in condition monitoring of the total system and servicing of its components. Condition monitoring is defined as the continuous or periodic measurement and interpretation of data to indicate the condition of a component to determine the need for replacement or servicing. Condition monitoring therefore deals with the acquirement of data (**d**ata **acq**uisition or DAQ) from sensors, the interpretation of that data (**da**ta **m**ining or DAM) and with taking corrective actions (ACT) on components that are to fail, thus preventing fail systems from developing and propagating. The basic concept of condition monitoring is to identify subtle changes in operation, such as increased vibration levels, that indicate a mechanical (or electrical) problem is starting to develop. These early messages provide more time to plan for machine downtime and repair.

There are four typical types of maintenance:

1) *preventive maintenance* - calendar based, i.e. activities are planned depending on working hours or at certain time intervals (scheduled maintenance); it may be based on observed deterioration of components; nothing is repaired but preventive jobs are done.
2) *random maintenance* – opportunity based, i.e. maintenance is done when the opportunity arises; the decision to maintain a component based on opportunities may or may not be triggered by the condition of a component.
3) *corrective maintenance* – emergency based, i.e. repairing when a component malfunctions; this may cause a general shutdown of the system; the repair activity was not scheduled beforehand.
4) *predictive maintenance* – condition based, i.e. components are being monitored and when irregular factors are discovered, one waits until a maintenance opportunity arises; it is a planned and corrective maintenance.

From the above given four types of maintenance it is clear that only a predictive maintenance concept qualifies for application in an intelligent

maintenance system that enables maintenance automation. Intelligence here is defined as the ability to make decisions based on information gathered through sensors in the equipment or provided by the control system of the total transport system.

Applied to belt conveyor systems the information gathered from a system is information on the life expectancy of individual components as for example idler rolls. This information leads to a decision either to inspect a certain idler station and its rolls more frequently or to change a roll for a new roll. Repairing in fact here means changing one roll for another. Whether or not a roll can be repaired and the effect of that on the belt conveyor's performance is outside the scope of this study.

The main issue in this study is the question how an automated inspection strategy is affected by the accuracy of the data acquired. In theory there are two outer limits in predictive maintenance. The first is that no accurate information of the rolls is available at all, basically meaning that an assessment of the remaining lifetime is made purely on the basis of historical data provided by the roll or bearing manufacturers (predictive maintenance based on statistics). The second is that during inspection very accurate information on the status of rolls is generated enabling an accurate assessment of the remaining lifetime of an individual roll (predictive maintenance based on data). A logistic simulation model is made to determine the effect of the accuracy of data acquired on automated inspection strategies. This model is discussed in Section 5.

3 Existing inspection systems

One problem faced with inspection or condition monitoring of components of belt conveyors, including the belt, pulleys and idler rolls, is that they rotate. Since the condition of components like rolls and pulleys can only be assessed when they are rotating, only condition monitoring systems based on vibration analysis or acoustical monitoring can be used. The opposite holds for the belt. The belt's condition can only be inspected when the belt conveyor system is not operating. Either way, an inspector has to walk the full length of the conveyor to inspect its components. An associated problem is that pulleys may be far apart from each other or that the conveyor has a great length. To ease inspection in these cases a powered maintenance trolley can be used for inspection purposes.

The concept of a powered maintenance trolley is not new. An early example of a maintenance trolley used on a belt conveyor system was the trolley used on the 100 km Phosboucraa overland system built by Krupp in the 70-ties to transport raw phosphate across a distance of 100 km from inside the west Sahara across a desert of stones to the loading point on the coast. This long-distance conveyor system, consisting of belt systems with centre distances of 6.8 to 11.7 km, applied a maintenance trolley concept

to allow for inspection, also see Figure 1. The Krupp-design turned out to be occasionally liable to instability.

Figure 1: *Powered maintenance trolley on Krupp system in Sahara.*

A revitalised version of a maintenance trolley is shown in Figure 2. This concept, designed and developed by CKIT[2] of South Africa, is quite robust and stable. It has been installed on a number of pipe conveyor systems, both inside and outside South Africa. It has three inspection platforms and is supported on six points (vertical and transverse direction). Current systems are powered from the main platform by combustion engines. Today's trolleys are all men operated and inspection and servicing work is carried out by men as well.

Figure 2: *CKIT concept of powered maintenance trolley.*

The concept of the maintenance trolley as developed by CKIT is adapted in this study as the platform for the further development of a fully automated maintenance facility. This development is divided in three stages.
The first stage will be the development of a maintenance robot on the trolley, enabling both automated inspection and servicing. The design of such a robot, which is a research project carried out at the section of

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[2] CKIT stands for Conveyor Knowledge & Information Technology

Transport Engineering and Logistics of Delft University of Technology, is not considered in this paper. The second stage is the implementation of the automated inspection routines as will be described in Section 5. The third stage is the full integration of the automated maintenance trolley in the total system's control system.

4 Data acquisition and mining

Condition monitoring techniques generally include one or several alarms that go off when a working point is exceeded or when a trend deviates from the expected values in time. References of the working points of signals are provided by knowledge-based systems and not by comparison with a model of the system. Signals are acquired by sensor systems.

4.1 Data acquisition techniques

Choosing the proper data acquisition technique has a large impact on the efficiency of the maintenance strategy. Good, reliable measurements, as well as proper analyses of the results of those measurements, are essential for reliable actions of the maintenance system. For rotating components most often a signal-based condition monitoring system is applied based on vibration and/or acoustics measurement techniques. Another option is using force and torque measurements as a basis for condition monitoring. For rotating components however, the application of wireless torque measurement equipment is required, which is expensive. It is suitable as a temporary monitoring system but today still not fit for large-scale permanent monitoring systems.

Spectral analysis is an important tool in vibration based condition monitoring. In general vibration based monitoring means measuring acceleration levels using three-dimensional accelerometers. The signal acquired from these sensors therefore is acceleration as a function of time. In a spectral analysis this signal is transformed from the time domain to the frequency domain by applying a Fast Fourier Transform technique (FFT). With the signal in the frequency domain the root source of the signal can be easily determined. The analysis of the spectral density, which relates the energy in the vibration signal to a specific frequency, is a good means of determination of faults advancing in time.

Vibration analysis is one of the main forms of condition monitoring and, in general, is often applied in the industry. The spectral density of vibration levels of a good working component will generally be low. When wear-out occurs, or when loads appear on specific components, then some small but notable changes will occur in the dynamical behaviour of the component. By making these changes visible and analysing them, a diagnosis of the problem can be made.

The monitoring techniques used in practice can be divided into two main categories:

- signal RMS[3] based monitoring
- detailed signal spectrum based monitoring

Acoustical analysis strongly resembles vibration analysis.

Data mining follows after data acquisition. Data mining consists of three main steps. The first step is the detection of defects that is based on knowledge of the dynamics of the components monitored. The second step is data processing, transforming the acquired data in data that is better fit for analysis. The third step is the actual analysis of the data itself required to make a decision to take certain actions.

4.2 Data mining I – detection of defects

In this paper the main focus is on bearings since bearings are, by far, the major source of the malfunctioning of rotating components including idler rolls. Obviously, idler rolls can also fail as a result of shell wear. The mechanism of shell wear however differs from bearing wear and as such requires a different detection procedure. In this paper only the detection procedure for bearing failures is discussed.

There are many ways in which bearing dynamics, which may lead to defects, can be classified. One of them is by defining component frequencies as a function of the rotating speed f_{rot} and of some geometry parameters including the number of rolling elements N, the diameter of the rolling elements D, the contact angle φ, and the bearing pitch diameter P. The frequencies identifying the four main dynamic effects in bearings are:

1) the cage rotational or the fundamental train frequency f_{cage}:

$$f_{cage} = \frac{1}{2}\left(1 - \frac{D}{P}\cos\varphi\right)f_{rot} \tag{1}$$

2) the inner ring or ball pass inner ring frequency f_{ir}:

$$f_{ir} = \frac{N}{2}\left(1 + \frac{D}{P}\cos\varphi\right)f_{rot} \tag{2}$$

3) the outer ring or ball pass outer ring frequency f_{or}:

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[3] RMS means Root Mean Square.

$$f_{or} = \frac{N}{2}\left(1 - \frac{D}{P}\cos\varphi\right)f_{rot} \tag{3}$$

4) the rolling element or ball spin frequency f_{re}:

$$f_{re} = \frac{P}{2D}\left(1 - \left(\frac{D}{P}\right)^2 \cos\varphi^2\right)f_{rot} \tag{4}$$

Bearing defects show up as an increase in spectral density for defect related frequencies. Bearing defect frequencies are a result of impacts due to the rolling elements passing over the defects as they pass through the loaded zone of a bearing. The defect frequencies, except for the cage rotational frequency, are surrounded by sidebands in a real signal. If the defect frequency originates from a signal that passed the loaded zone, there are k sidebands where $k \in N$. The next frequencies could appear in a spectrum:

1) outer ring defect: at $f = nf_{or} \pm kf_{rot}$ (5)

2) inner ring defect: at $f = nf_{ir} \pm kf_{rot}$ (6)

3) rolling element defect: at $f = nf_{re} \pm kf_{rot}$ (7)

4) cage defect: at $f = nf_{cage}$ (8)

where n is the number of harmonics.

As the defect is smaller, the measured acceleration signal is more like a pulse than like a sine wave and the energy content decreases while the defect frequency increases in the spectrum.

4.3 Data mining II – technique of data processing

Band enveloping is the process of transforming a vibration signal with small superimposed disturbances into isolated disturbance information. The main reason for using an envelope of a signal is that one can detect developing defects like small cracks in a very early stage. The process of band enveloping consists of three steps: high-pass filtering, rectification, and low-pass filtering.

As the energy of a disturbance compared to the energy of the sine wave is very low then the pulse is hardly detectable in the frequency spectrum.

The first step therefore is to use a high-pass filter to filter out the (low frequency) sinusoidal component.

The remaining signal contains only the repetitive disturbances. The signal then is rectified and passed through a low pass filter. The peak in the frequency spectrum then represents the defect frequency of the component that is defective. The pulses lose the high frequency components because of the low-pass filter. The repetition period however remains.

4.4   Data mining III – data analysis

Data analysis can be quite complicated. If the scope of analysis is restricted to bearings and the four identified possible defects as listed Section 4.2, then the procedure can be as follows. First the frequency spectrum is scanned for anomalies. If peaks are detected in this spectrum then the equations (5) till (8) can be used to identify the root cause. Knowing the root cause, for example outer ring problems, then the acquired signal level is compared to a data base identifying the seriousness of the defect(s) and determining a proper course of action. Part of the latter determination is based on common if-then-else structures enabling a structured (and automated) analysis of possible causes and future effects on operation. If more than one possible cause for a defect is known, for example a specific signal can identify a defect in a bearing but also in the sensor itself, then confidence factors have to be applied to rule-out the most possible cause.

5   An intelligent maintenance concept

In this section a concept for the logistic control of an intelligent maintenance system is given. The maintenance concept is based on the predictive maintenance concept, using either statistics or the results of a detailed data analysis, which was introduced in Section 2. The technical lay-out of the maintenance system is based on the application of an automated maintenance trolley including a monitoring and servicing robot as discussed in Section 3. The data acquisition and mining techniques used were discussed in the previous section.

5.1   Model

In the logistic model a number of elements are detailed including:

- the belt conveyor itself,
- the bearings,
- the maintenance robot,
- the inspection requirements,
- the servicing aspects,
- and the data analysis.

5.1.1 Belt conveyor

In the model the belt conveyor can be specified in terms of its length and the idler pitches. The number of idlers then is calculated automatically assuming that the pitch is constant. It is assumed that a carrying idler has 3 rolls and a return idler 2. Each roll has two bearings, which have a minimum life length as specified by the roll and bearing manufacturer. The number of the rolls that fail before the minimum life length can be specified. As a standard this number is 10%. If on a system used rolls, instead of new rolls, are installed then the program accounts for this effect by allocating remaining life lengths to individual rolls.

5.1.2 Bearings

The life length of a specific bearing in a roll is allocated via a tabularized distribution. Under and upper limits can be specified assuming a uniform distribution (minimum and maximum life length as specified by roll and bearing manufacturer). The chance of failure before reaching the minimum life length can be specified, again according to a uniform distribution. All distributions can be changed for the middle and the side rolls of the carrying as well as the return idler sets.

5.1.3 Maintenance robot

The maintenance robot travels over the structure of the belt conveyor in the direction from the head to the tail at a constant speed. It is assumed that the robot is available 24 hours per day.

5.1.4 Inspection

On inspection of an idler set, the total life length estimation of an individual roll is based either on historical data (statistics) or based on accurate vibration measurements. The total inspection time consists of a fixed set-up time and the inspection time itself. All rolls in one idler set are inspected at the same time using a multiple sensor robot arm.

5.1.5 Service

If the maintenance robot decides to change a roll then it is always replaced by a roll of the same type. The total reparation time consists of a fixed set-up time and the time for repairing or, in this case, changing out the idler roll.

5.1.6 Estimation of residual lifetimes

The robot estimates the lifetime of a roll using a Fourier analysis of the vibrations in the roll. For simulation of this process, a model with 2 parameters is used. The estimation is a sample from a normal distribution

with as mean the lifetime of the roll. The deviation of this distribution determines the accuracy of the estimation and is controlled by the first parameter (d). With the second parameter (f), a bias is introduced. The estimator becomes conservative, biased towards underestimating the lifetime.

The estimator S_1 is defined by:

$$S_1 \;=\; L + d(L - A)X - f\,(L\text{-}A) \tag{9}$$

Where   L, Lifetime of the roll
               A, Current age of the roll
               X, Random variable, sampled from a Normal(0,1)-distribution
               d, Deviation, as fraction of the residual lifetime
               f, Safety factor, as fraction of the residual lifetime

A sample of X is drawn for the normal distribution each time estimation is required. If f equals zero then estimator is unbiased. The probability that the estimator overestimates the lifetime is 50 %. With f > 0 the estimator becomes biased towards underestimating the lifetime.

Both deviation and safety factor are a fraction of the residual lifetime (L - A). This means that when the age of the roll reaches its actual lifetime, the deviation and the bias of the estimator both become zero. When the age equals the lifetime, the estimator S_1 is 100 % accurate.

The effect of different values for d and f on the behavior of the estimator can be seen in Figure 3. If f equals zero, 50 % of the estimations are overestimating the lifetime. This could result in late replacement of a roll, which is unwanted. By increasing f, the estimation becomes biased, conservative. However, if f is too large, chances are that the estimation will drop below the actual age (as marked by the line x=y). This will result in an unnecessary early replacement of the roll.

The proper value for d depends on the physical properties of the robot and must be determined experimentally. Then, the simulation model can be used to determine the optimal value for f.
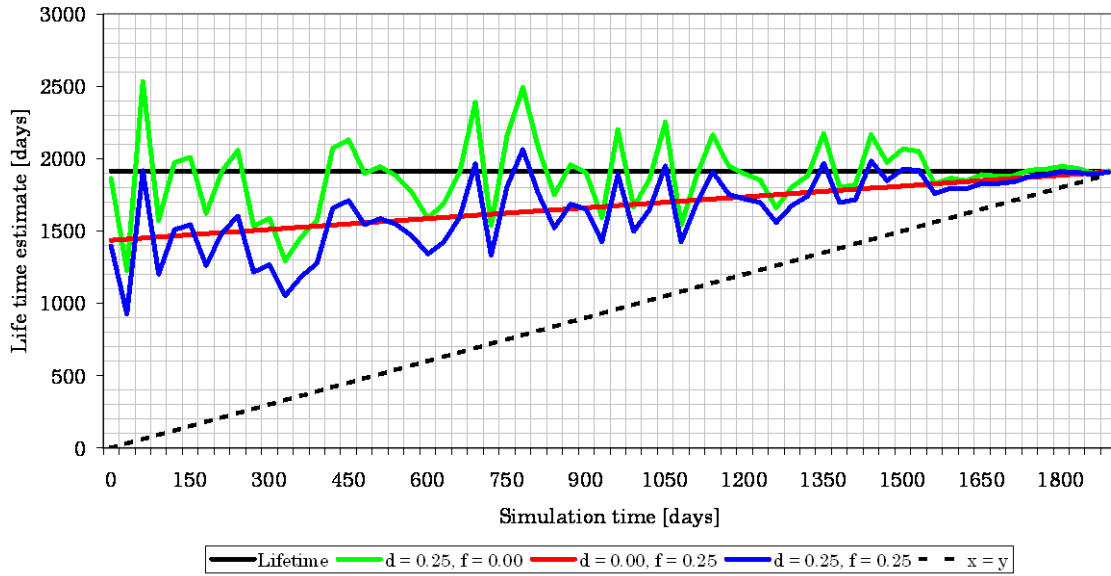
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Figure 3: *Behaviour of the estimator for different values of d and f.*

5.2 Planning and control

5.2.1 Maintenance strategies

In theory, the maintenance robot can perform inspections both on regular as well as non-regular time intervals. In this study it was assumed that the robot is inspecting the conveyor belt at fixed time intervals. Whether or not the use of a non-regular time interval is beneficial depends among other things on the ratio between the time the trolley needs to travel the conveyor versus the inspection interval time. The travel time is not only determined by the length of the belt conveyor but by the number of inspections, inspection and servicing time.

The cycle interval time must be specified in case of regular timed inspection intervals. Each cycle, the robot travels the entire conveyor belt first forward to the end, then back the beginning of the belt. During the cycle, different strategies are possible. Four strategies are considered in this paper:

Strategy 1: *Inspection only forward, data mining immediately after inspection, servicing if required. Do nothing on return.* It is assumed that the maintenance trolley has sufficient data processing equipment on board to perform the data mining function.

Strategy 2: *Inspection and servicing both forward and on return. Data mining right after inspection.* It again is assumed that the

maintenance trolley has sufficient data processing equipment on board to perform the data mining function.

Strategy 3: *Inspection only forward, servicing only on return. Data mining after inspection but before return.* In this case data mining is still done on board of the maintenance trolley, either during inspection or upon arrival at the tail of the system.

Strategy 4: *Inspection only forward, data mining upon arrival at the tail, servicing on return.* In this case data has to be transmitted to a central computer system that, after processing the data, dispatches a servicing list to the trolley.

Note that it is not explicitly assumed that the servicing function is performed by a maintenance robot, it may be performed by men as well. In the latter case the servicing time and cost obviously change, the inspection strategy remains the same.

5.2.2 Safety Time

The safety time defines the time interval before the end of the (estimated) lifetime in which a roll is replaced by the robot. If the safety time is too large, the rolls might be replaced too soon which is unwanted. If the safety time is too small, the rolls will be replaced too late, which is even worse. The safety time should at least equal the cycle interval time.

5.2.3 Inspection time

Whether a roll is inspected or not depends on the inspection strategy. With a fixed inspection strategy, each roll is inspected each cycle of the robot. This will result in long cycle times for the robot and a lot of unnecessary inspections. Therefore, a flexible inspection strategy defines the inspection time. The inspection time defines the time interval before the end of the (estimated) lifetime in which a roll must be inspected by the robot.

An idler frame in the conveyor will be inspected if at least one of the rolls is in its inspection interval. If a frame is inspected, each roll in the frame will be inspected. Thus, even a roll which is not in its own inspection interval will be inspected several times, resulting in a more accurate estimation of the lifetime.

5.3 Simulation settings

This section lists the settings used in the simulation.

5.3.1 Conveyor

The length and frame distance determines the number of frames and the number of rolls in the conveyor system.

Length	10,000 m
Frame distance	2 m
resulting number of frames	5001
resulting number of rolls	21671

Table 1: *Conveyor settings.*

5.3.2 Bearings

The lifetime of a bearing is distributed uniformly between LMin and LMax. A certain rate of the bearings fails between 0 and LMin. This failure is uniformly distributed between 0 and LMin. From these specifications the average lifetime of each type of bearing can be calculated. The lifetime of a roll is the minimum of the lifetime of two bearings.

Life time distribution	LMin	LMax	Failure rate	Average
Upper, side rolls	1750 days	2083 days	0.10	1812.4 days
Upper, middle roll	1667 days	2000 days	0.10	1733.5 days
Lower, Side roll	1875 days	2208 days	0.10	1931.1 days

Table 2: *Bearing settings.*

5.3.3 Robot

The robot moves with a constant speed. The total inspection time is the sum of a fixed setup time and the actual inspection time. The total servicing time is the sum of a fixed setup time and the actual servicing time.

Speed	0.5 m/s
Inspection setup time	30 sec
Inspection time	60 sec
Servicing setup time	30 sec
Servicing time	240 sec

Table 3: *Robot settings.*

5.3.4 Strategy

The robot strategies are discussed in paragraph 5.2.1. Below the settings for the experiments are summarized.

Inspection and reparation forward only	
Inspection strategy	Flexible

Table 4: *Strategy settings.*

5.3.5 Simulation settings

Simulation run length and the random seed value (value required to start the simulations) are found in the table below.

Run length	3650 days
Random seed value	54321

Table 5: *Simulation settings.*

5.3.6 Performance indicators

The performance of the maintenance robot is determined by two factors. Most important is the number of rolls that are replaced too late. Too late replacement means that the roll already broke; this could cause damage to the conveyor belt. The other performance indicator is the average time between replacement and lifetime of the roll. Replacing rolls with a large residual lifetime is a waste. The following results are presented:

- Average cycle time for the robot
- Average number of inspections per cycle
- Percentage of early replaced rolls
- Average time between early replacement and lifetime roll
- Percentage of late replaced rolls
- Average time between lifetime roll and late replacement

The performance is summarized with two performance indicators:

Failure : percentage of rolls replaced (too) late
Waste : average time rolls are replaced before the end of their lifetime

5.3.7 Experiments

The following experiments have been performed:

Value for deviation d : 0.00, 0.10, 0.20

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Value for safety factor f   : 0.00, 0.25
Robot cycle interval   : 30 days, 15 days
Safety time   : equals cycle interval
Inspection time   : twice the safety time

5.4 Simulation results

This section lists the result of the series of simulations performed.

5.4.1 Deviation in lifetime estimation

Settings					Cycle		Early replaced		Late replaced	
d	f	Cycle interval	Safety Time	Inspection Time	Avg. Time	Nr Inspect	% Early	Avg Early	% Late	Avg Late
0.00	0.00	30	30	60	2.40	3308	100%	15.2	0%	0.2
0.10	0.00	30	30	60	2.39	3313	87%	15.7	13%	26.9
0.20	0.00	30	30	60	2.38	3332	77%	16.9	23%	43.1

Table 6: *Results with different values for the deviation with f = 0.*

In the first series of simulations the safety factor f was set to zero. From Table 6 it can be concluded that the deviation in lifetime estimation (factor d) is crucial for the success of a maintenance robot. The smaller the deviation d, the better the performance. If the deviation is zero, the estimations are always exact, and 0% of the rolls is replaced late. However, a deviation of zero is not realistic in practice; the estimator is not perfect. A deviation above zero introduces failure.

5.4.2 Safety factor in lifetime estimation

Settings					Cycle		Early replaced		Late replaced	
d	f	Cycle interval	Safety Time	Inspection Time	Avg. Time	Nr Inspect	% Early	Avg Early	% Late	Avg Late
0.00	0.25	30	30	60	3.05	6011	100%	24.9	0%	0.0
0.10	0.25	30	30	60	3.02	5876	100%	25.4	0%	0.0
0.20	0.25	30	30	60	2.94	5571	99%	26.8	1%	15.7

Table 7: *Results with different values for the deviation with f = 0.25.*

In the second series of simulations a safety factor of 0.25 was introduced. Defining a safety factor f reduces the percentage of late replaced rolls (failures) significantly. Comparing Table 6 and 7 shows that the "price" for less late replaced rolls is an increase in the number of inspections (7th column – 3308 versus 6011), and an increase in early-replaced rolls (waste) by circa 10 days (9th column – 15.2 days versus 24.9 days).

5.4.3 Inspection cycle interval

Settings					Cycle		Early replaced		Late replaced	
d	f	Cycle interval	Safety Time	Inspection Time	Avg. Time	Nr Inspect	% Early	Avg Early	% Late	Avg Late
0.10	0.25	30	30	60	3.02	5876	100%	25.4	0%	0.0
0.10	0.25	20	20	40	2.25	4288	100%	17.0	0%	0.0
0.10	0.25	10	10	20	1.44	2462	100%	8.5	0%	7.5
0.10	0.25	5	5	10	0.98	1380	100%	4.2	0%	8.8

Table 8: *Results with different cycle interval settings.*

In this series of simulations the deviation d was set to 0.10 and safety factor f to 0.25. The variable here was the inspection time. Table 8 shows that shortening the inspection cycle interval leads to less waste. The percentage late replaced rolls remains 0%, while the number of days, the rolls are replaced before end of lifetime, is reduced from 25 days at a cycle of 30 days to 4 days at a 5 day cycle. With a men-operated trolley changing the number of inspections and moves of the trolley is rather expensive, with an automated trolley the additional costs are only related to power and data processing time.

5.4.4 Fixed versus flexible inspection plan

Settings					Cycle		Early replaced		Late replaced	
d	f	Cycle interval	Safety Time	Inspection Time	Avg. Time	Nr Inspect	% Early	Avg Early	% Late	Avg Late
0.10	0.25	30	30	60	3.02	5876	100%	25.4	0%	0.0
0.10	0.25	30	30	fixed	6.86	21671	100%	25.3	0%	0.0

Table 9: *Results with flexible and fixed inspection.*

To determine the effect of flexible versus fixed inspection intervals (smart inspecting versus inspecting every move), one more simulation was performed with a fixed inspection time equal to the cycle time. The use of a flexible inspection plan does not influence the performance of the system in terms of early replaced rolls. The average early replacement is almost the same, compared with a fixed inspection. The number of inspections during a cycle however is reduced by almost a factor 4. Further, it is expected that with large deviations (for instance d > 0.25) a fixed inspection plan may be needed to reduce failure.

6 Conclusions and recommendations

From the analyses given in this paper it can be concluded that the technology to set-up an automated maintenance system for belt conveyors based on the trolley concept is available. It has been shown that a proper logistic model as given in section 5 is required for the intelligent control of the maintenance trolley and robot, maximizing their performance.

The performance level depends on the accuracy of the remaining life estimation. It was shown that the settings of the deviator d and the safety factor f are important for the performance of the maintenance robot. Most important therefore is to gain further insight in the physical system of maintenance robot and conveyor belt. If the characteristics of the inspection robot are known, the model for the lifetime estimator in paragraph 5.1.6 can be evaluated and the best setting for the parameters d and f can be chosen. However, it is important to realize that the maintenance strategies also work in case the life estimator is based on historical data provided by roll/bearing manufacturers. In that case however, the number of inspections as well as early replaced rolls will increase significantly.

If the model is validated to represent the physical system of robot and conveyor, more work can be done to improve the maintenance schedules. Further recommendations therefore are to:

- Optimize the values for cycle interval, safety time and inspection time
- Use flexible cycle times for inspection instead of a fixed cycle interval
- Introduce fixed inspection rounds with low frequency (cycle time >> 100 days), and use the flexible inspection strategy in between
- Use statistical methods (exponential smoothing, moving average) to improve the lifetime estimators during the lifetime of a roll
- Introduce new strategies; for instance, decouple inspection and repair rounds (for cases where inspection can be automated and repair is manual)

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