Minerals Engineering 53 (2013) 1–8

Contents lists available at ScienceDirect

Minerals Engineering

journal homepage: www.elsevier.com/locate/mineng

Remaining useful life prediction of grinding mill liners using an artificial neural network

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A R T I C L E I N F O

Article history:
Received 6 April 2013
Accepted 30 May 2013
Available online 5 August 2013

Keywords:
Remaining useful life
Artificial neural network
Principal component analysis
Wear prediction
Maintenance scheduling
Mill liners

A B S T R A C T

Knowing the remaining useful life of grinding mill liners would greatly facilitate maintenance decisions. Now, a mill must be stopped periodically so that the maintenance engineer can enter, measure the liners' wear, and make the appropriate maintenance decision. As mill stoppage leads to heavy production losses, the main aim of this study is to develop a method which predicts the remaining useful life of the liners, without needing to stop the mill. Because of the proven ability of artificial neural networks (ANNs) to recognize complex relationships between input and output variables, as well as its adaptive and parallel information-processing structure, an ANN has been designed based on the various process parameters which influence wear of the liners. The process parameters were considered as inputs while remaining height and remaining life of the liners were outputs. The results show remarkably high degree of correlation between the input and output variables. The performance of the neural network model is very consistent for data used for training (seen) and testing (unseen).

1. Introduction

Today's industries are increasingly using condition based maintenance (CBM) to minimize breakdowns and their impact on performance, reduce maintenance intervals and consequent costs, improve production efficiency, and ensure safety. The development of a maintenance system with intelligent features in fault detection and knowledge accumulation for mechanical structures is a goal for researchers; such a system would greatly assist industries, as it is now almost impossible to manually analyze rapidly growing data to extract valuable decision-making information. In recent decades, a great deal of research has sought methods of predicting or estimating the remaining useful life (RUL) of critical components in various industries. Knowing the RUL of an asset has an impact on planning maintenance activities, spare parts provision, operational performance, and profitability (Jardine et al., 2006; Altay and Green, 2006; Elwany and Gebraeel, 2008; Wang et al., 2009; Kim and Kuo, 2009; Papakostas et al., 2010).

Ore grinding mills are heavy duty pieces of equipment that work 24 h a day in highly abrasive environments. From an economic point of view, it is important to keep these mills in operation and minimize the downtime for maintenance or repair, because a drop in production caused by a both scheduled and unscheduled stoppages lead to monetary losses. The auto-genus mill which is used in mineral processing is important for particle size reduction and high metal recovery. Among its most critical components are the liners which protect the mill's shell and are used to lift the charge (ore) inside the mill, thus enhancing grinding performance, Fig. 1. Because their wear influences the grinding performance in the context of metal recovery, the mill needs to stop occasionally for the maintenance engineer to enter the mill and measure the wear, but each stoppage leads to heavy production losses. The significant impact of mill liners on the monetary return for the mill owner has led to studies of maintenance activities performed on mill liners, such as wear measurement, replacement and maintenance scheduling.

Although many studies have been carried out on the effect of mill liners on grinding mill performance (Cleary, 2001; Santarisi and Almomany, 2005; Kalala et al., 2008; Yahyaei et al., 2009; Dandotiya and Lundberg, 2012), the ability to predict or measure the liners' wear without stopping the mill has not been considered. Therefore, the main focus of the present research is optimization of wear measurement, as well as RUL predictions for optimal replacement and maintenance scheduling to maximize both performance and profits.

A review of approaches to RUL prediction shows that an artificial neural network (ANN) is a powerful tool; it can readily address modeling problems that are analytically difficult and for which conventional approaches are not practical, including complex physical processes with nonlinear, high-order, and time-varying dynamics and those for which analytic models do not yet exist. Zhang and Ganesan (1997) used a self-organizing neural network for multivariable trending of fault development to estimate the

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0892-6875/$ - see front matter
http://dx.doi.org/10.1016/j.mineng.2013.05.026

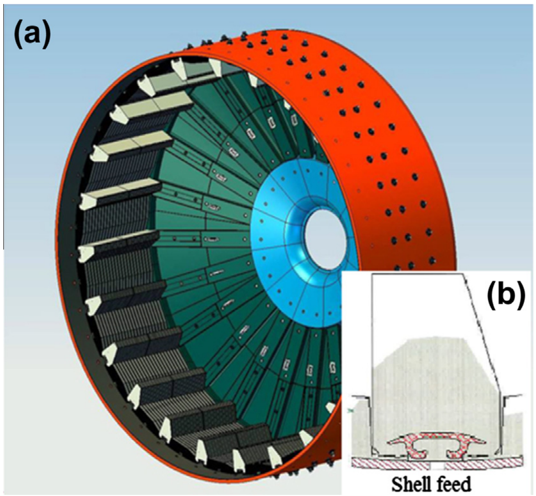

Fig. 1. a Mill liners inside the mill, (b) shell feed lifter bars.

RUL of a bearing system. Shao and Nezu (2000) proposed a new concept called a progression-based prediction of remaining life to estimate the RUL of a bearing. This concept manipulated the variables determined from online measurements via a compound model of a neural network. Byington et al. (2004) developed a neural network for remaining life predictions for aircraft actuator components. Yu et al. (2006) presented a neural network model to predict behavior of a boring process during its full life cycle. Mazhar et al. (2007) estimated the remaining life of used components in consumer products by using artificial neural networks. Runqing et al. (2007) dealt with residual life predictions for ball bearings based on a self-organizing map and back propagation neural network methods. Similarly, Huang (2007) proposed a method to predict a ball bearing's RUL based on a self-organizing map and back propagation neural network methods. Gebraeel and Lawley (2008) developed a neural network to estimate the RUL of rolling element bearings by monitoring their vibrations. In this study, ANN has been applied to predict the RUL of the liner with respect to the remaining height and remaining life.

The paper is organized as follows: Section 2 describes the data collection; Section 3 explains methodology; results and discussion are provided in Section 4. Section 5 offers a conclusion.

2. Data collection

For the mill liners, the development of an RUL assessment based on life cycle data analysis is hampered due to the unavailability of operating information, particularly for the wear out phase of liner measurement. The lack of accurate data for this part of the liner could have hampered the study. However, data requirements were fulfilled by selecting the shell feed (type1 of the lifter bar (LB1); see Fig. 1b) of the liner from 2008 to 2011 for two life cycles.

2.1. Data sources

The following sources were used to gather condition monitoring (CM) and process data:

- Metso mineral for wear measurement CM data.
- Boliden mineral for affecting factors (process data).

Utmost care was taken to ensure that the collected data were as accurate as possible. There were no data for some periods; in other periods, the grinding mill worked only a few hours per day, etc. We sought to determine why these occurred.

2.1.1. Data from Metso mineral

For this study, an important source of raw data on liner maintenance, inspection and replacement schedule was Metso minerals. The most difficult part was collecting data on liner wear because there were fewer measurements. Because total value of lost production during any mill stoppage is extremely high, it is not economical to stop the mill at intervals and measure liner wear, except for maintenance, inspection, installation, replacement. Thus, data were collected over different life cycles (from one installation to the next replacement). The solid circles and triangle in Fig. 2 show LB1 remaining height and remaining life during one life cycle; other data are generated by an interpolating technique, Piecewise Cubic Hermite Interpolating Polynomial (PCHIP) and Spline. PCHIP is the best choice for this study, because it finds values of an underlying interpolating function at intermediate points. It also preserves the shape of the data and respects monotonicity, and these data have monotonically deceasing characteristics.

2.1.2. Data from Boliden mineral

Raw process data on the grinding mill, collected from the Boliden mineral databases, were treated to extract the information used in the models. Information on the important influencing factors for liner wear was collected in discussions with expert personnel and engineers from the mining company. These data include the ore type, ore feed (tonne/h), power (kW), angular speed (% of centrifugal critical speed), torque (% of the max torque), water addition (m^3/h), grinding energy (kW h/tonne), load (tonne). This information comprised the practical complexities of the grinding process inside the mill, including physical explanations of the

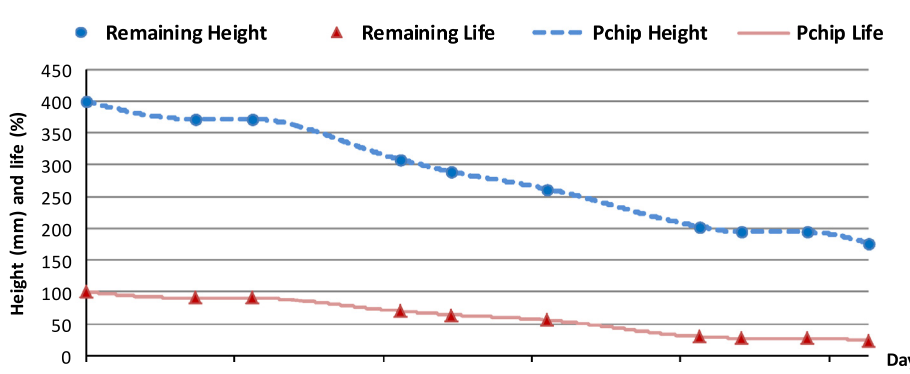

Fig. 2. Generated remaining height and remaining life data by PCHIP interpolating method.