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Unscented Kalman filter for a coal run-of-mine bin ⋆

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Abstract: This paper describes the application of an unscented Kalman filter to a coal run-of-mine bin. A dynamic model of the bin is derived using the principle of mass conservation. The dynamic model is nonlinear with unknown parameters that are identified using actual plant production data. The identified dynamic model is used by an unscented Kalman filter to update the states of the system to improve model output accuracy. The derived bin model with and without an unscented Kalman filter is compared with actual plant data. Results show that the unscented Kalman filter can significantly improve the plant outputs estimated by the bin model on its own.

Keywords: unscented Kalman filter; coal feed bin; dynamic modelling; system identification.

1. INTRODUCTION

This paper investigates the use of an unscented Kalman filter (UKF) for a coal run-of-mine bin. Although this specific application is for a coal bin, the concept can also be applied to other mineral processing storage or buffer facilities. The bin in this specific case has a single measured disturbance feed with three streams where coal can be reclaimed. Two of the three reclaiming streams can be controlled automatically while the third stream is opened manually through the use of a flap gate. The approach that is followed in this paper is to obtain or derive a greybox model that is sufficient for control purposes. The use of a state estimator such as the UKF is simulated to show how the dynamic model can be used in practice. Ultimately the dynamic model with UKF could be used in a model-based controller. However, this is beyond the scope of this paper.

Literature that was found on storage and buffer mathematical modelling concentrates on the modelling of flow patterns of material within the vessel. Sielamowicz et al. (2014) used linear and nonlinear regression to model the eccentric flow of material within a silo. Dynamic load modelling of cyclic flow of bulk solids during gravity discharge in bins has also been developed in detail (Roberts and Wensrich, 2002; Chen et al., 2005; Tüzün and Nedderman, 1985).

Other mathematical models of bins make use of finite element analysis to describe the three-dimensional flow of material within the vessels. Constitutive models have been developed from material tests and used in finite element calculations for static wall pressures for the prevention of silo damage from coal (Ooi et al., 1996). Discrete element methods are also used to describe the mechanical behaviour of material filling and emptying in silos (González-Montellano et al., 2011, 2012).

Given the limited availability of dynamic models for bins from the available literature, the process dynamics of the bin is modelled using the principle of mass conservation (Stephanopoulos, 1984). The dynamic model developed is nonlinear and has various associated unknown parameters. These unknown parameters are determined through system identification techniques described in Ljung (1987). By identifying the unknown parameters with actual plant data the model fit is determined.

In order to the increase the accuracy of the model fit, an observer is used. The specific observer used in this paper is the UKF. Various other nonlinear filters are available (Daum, 2005) such as particle filters, batch filters and exact recursive filters. Daum (2005) indicates that nonlinear filters usually provide vastly superior performance compared to the traditional Kalman filter. Particle filters make use of Monte Carlo integration using importance sampling for the prediction of statistical outputs. The Monte Carlo integration of Particle filtering will not be used for in paper. However, an example of particle filtering applied to a run-of-mine ore mill has been shown by Olivier et al. (2012b). Batch filters use numerical integration to solve for prediction of outputs over a single batch of data. This approach is similar to the system identification approach used in this paper. However, instead of solving for unknown states, unknown parameters are solved for. Exact recursive filters use numerical integration of ordinary differential equations (ODEs) to solve for sufficient statistics

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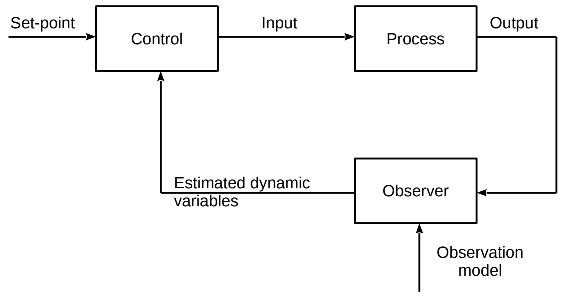

Fig. 1. General control loop (Simplified from Hodouin (2011).

in the exponential family of probability densities. The term "exact" implies that partial differential equations are transformed into ODEs where the Kalman filter is an example of this.

Daum (2005) describes the extended Kalman filter (EKF) and the UKF as different to the Kalman filter in that they do not apply only to linear-Gaussian problems. The EKF (Julier and Uhlmann, 1997) predicts outputs based on linear approximations of the process dynamics by simply using the first-order Taylor series expansion of the system state equations. The UKF does not use simple linear approximations like the EKF. The UKF (Wan and Van der Merwe, 2000) instead uses a more accurate approximation to evaluate the multidimensional integrals required. Since the dynamic bin model developed already has the form of nonlinear state equations, the UKF is applied to perform the state observations.

Hodouin (2011) describes methods for automatic control, observation and optimisation in mineral processing plants. Figure 1 indicates how a typical control system operates with a given observer. The observer uses measured output with an observation model to estimate dynamic variables for control. In this case the dynamic bin model can be used as an observer model. An observer such as the UKF can improve the estimation of the state variables for a control system. The improved state variable estimation is ideal for a practical implementation of a control system for the bin system as it can improve the accuracy of the state estimates fed to the controller.

Although many of the papers available in literature show the application of observers for estimation and control in minerals processing or the coal industry, no literature was found relating to coal bins for storage or buffer capacity. Herbst et al. (1992) have used a Kalman filter to estimate the ball and rock holdup for the model-based control of a semi-autonomous grinding mill. Olivier et al. (2012b) have shown how to apply both state and parameter estimation using dual particle filters and applied them to a run-of-mine ore mill. Further work on observers applied to milling include a fractional order disturbance observer and a Bode ideal cut-off observer (Olivier et al., 2012a). Wilson et al. (1998) describe experiences in implementing the EKF on an industrial batch reactor which is related to a specific chemical process. In the coal environment, Clarke et al. (1989) use a Kalman filter to estimate the load and pressure of coal-fired boilers. Pindyck (1999) show an interesting application where a Kalman filter was used to estimate the forecasting of oil, coal and natural gas prices.

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This paper initially describes the bin process flow and details the development of the dynamic model in Section 2. The identification of the unknown model parameters are also given. Section 3 describes the mathematical details behind the UKF. Section 4 shows the simulation results of the dynamic model with identified parameters and UKF simulated results. The comparison of the bin model output, with and without the UKF, is summarised in Section 5.

2. BIN PROCESS AND DYNAMIC MODEL DEVELOPMENT

This section provides a detailed description of the bin process flow and associated variables. The development of the dynamic model used to describe the material flow is then derived. The dynamic model developed is a nonlinear model with certain unknown parameters. The values for these parameters are estimated using actual plant production input-output data.

2.1 Bin process flow

The bin process is relatively simple, in that run-of-mine coal ore is fed into the bin while three product flow lines remove material from the bin. An illustration of the bin and process flow is shown in Figure 2. The geometry of the material within the bin has been simplified to a pyramid polyhedron shape. However, the material never reaches the apex of the pyramid. This means that when the silo is full, there is always a flat surface area representing the top of the stockpile. It was found that the proposed geometric shape fits better with the production data as opposed to a simpler constant horizontal surface area. The conical bottom sections are catered for by assuming the mass within them forms part of the two feeder systems ($f_{bf,1}$ and $f_{bf,2}$) and manually actuated bin mass flow rate ($W_{b,o,3}$).

Table 1 gives a description of the variables that have been used for the bin. The third product mass flow rate ($W_{b,o,3}$) is manually actuated through a chute flap gate. This flap gate is rarely opened and only used if material flow to a different plant area becomes too low. The remaining two product mass flow rates ($W_{bf,o,1}$ and $W_{bf,o,2}$) are actuated through vibratory feeders where the feeder motor speeds ($f_{bf,1}$ and $f_{bf,2}$) are varied by using variable speed drives.

The current problems and challenges relating to this piece of equipment are the accurate measurement and control of the bin level. It is possible for the bin to easily overflow and run empty during operation. The material flow further downstream is therefore affected and as a result the manually actuated chute flap ($W_{b,o,3}$) is opened to try and correct the material imbalance.

2.2 Model derivation

The dynamic model for the bin can be derived by using using the principle of mass conservation as detailed in