Development of weightometer soft sensor

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Synopsis

A prototype weightometer soft sensor is under development at DebTech, De Beers in partnership with Venetia Mine. Its main function consists of an online data source; data validation; dynamic weightometer models; online detection of weightometer failure; alarming and replacing a weightometer when it fails. Thirty-one dynamic models have been developed. All models with $R^2 \geq 85\%$ are accepted as good models and they generally have satisfactory results with a daily error of less than 8% within a 90% confidence level. By using those models, a set of soft sensors can be set up to cover all weightometers in the entire processes starting from primary crushing to the stock piles of dense medium separation (DMS).

Some practical issues and concerns on model development are discussed, including data collection, data analysis, data pre-processing, variable selection, time delay, model training and model validation. When deploying the weightometer soft sensor system, the potential benefits could include reduction in plant downtime; reduction in unplanned maintenance and even replacement of non-critical weightometers, particularly where nuclear weightometers are used.

Keywords: soft sensor, weightometer, dynamic modelling, neural network modelling

Introduction

The weightometer is one of the critical items used at De Beers' mines to measure ore/concentrate flowrate in ton per hour (tph). The weightometer readings are used to calculate efficiencies such as operational efficiency (Rand/ton-ore, or Rand/carat-diamond), plant production efficiency (ton-ore/day), and recovery efficiency (carat-diamond/ton-ore). The performance of weightometers is highly linked to the operational conditions, such as spillage of ore/concentrate on the weightometers and problems in conveyor operation.

In general, the conveyor weightometers used at De Beers' mines are within 99% of accuracy in terms of ton per hour (tph), according to weightometer suppliers' specifications. A typical weightometer, as shown in Figure 1, consists of three basic components: (1) load cells to measure the mass of the belt and ore/concentrate within a certain section, (2) a tachometer to measure the velocity of the belt, and (3) a calculation unit.

The calculation unit converts the mass of ore and the speed of conveyor into ore flowrate in tph. Some problems in conveyor operation can have a huge impact on the accuracy and reliability of weightometers, such as heavy vibration of belt, spillage of ore/concentrate from conveyor on to the weightometer mechanism. The error of weightometer readings can sometimes be as high as 20% at some of the ore treatment plants. Furthermore, it is very difficult to predict when a weightometer reading becomes bad. Therefore, it becomes essential to improve the accuracy and reliability of weightometer readings if one wants to measure and control operational efficiencies properly.

There are more than 30 weightometers used at a typical ore-treatment plant. It is a costly operation in practice, to keep all weightometers maintained properly, by means of steady calibration, dynamic calibration, and belt-cut calibration.

A soft sensor, a piece of software which has the same functions as a physical measurement sensor, is considered to be used to enhance the accuracy and reliability of the weightometers used at the mines. A prototype weightometer soft sensor (WSS) is currently under development by a joined team of DebTech and Venetia Mine.

During the past two decades, remarkable advances have been made in artificial intelligent techniques, such as neural networks, expert systems, and fuzzy logic. By using neural networks, an accurate model can be built to predict the outputs of a dynamic process with high non-linearity. This is the

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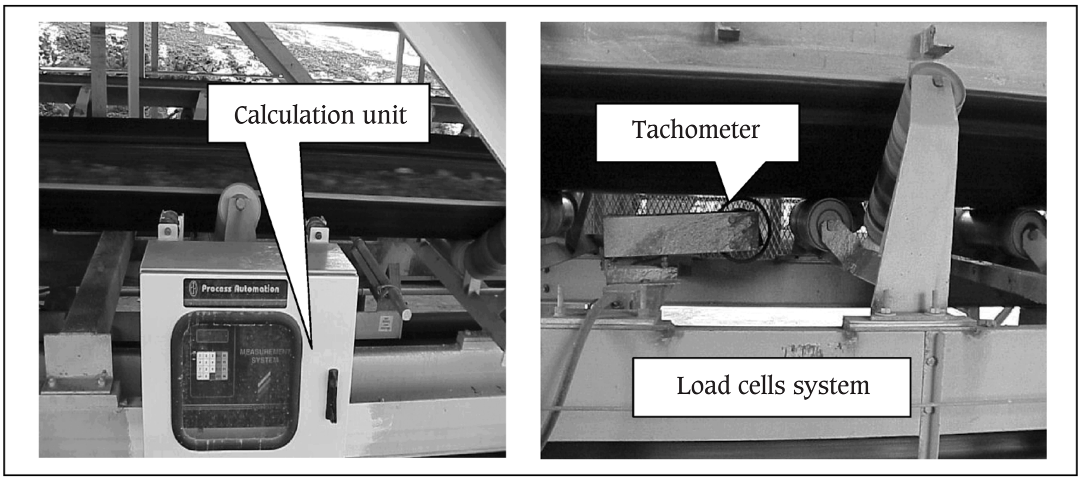

Figure 1—Typical conveyor weightometer consisting of load cells, a tachometer and a calculation unit

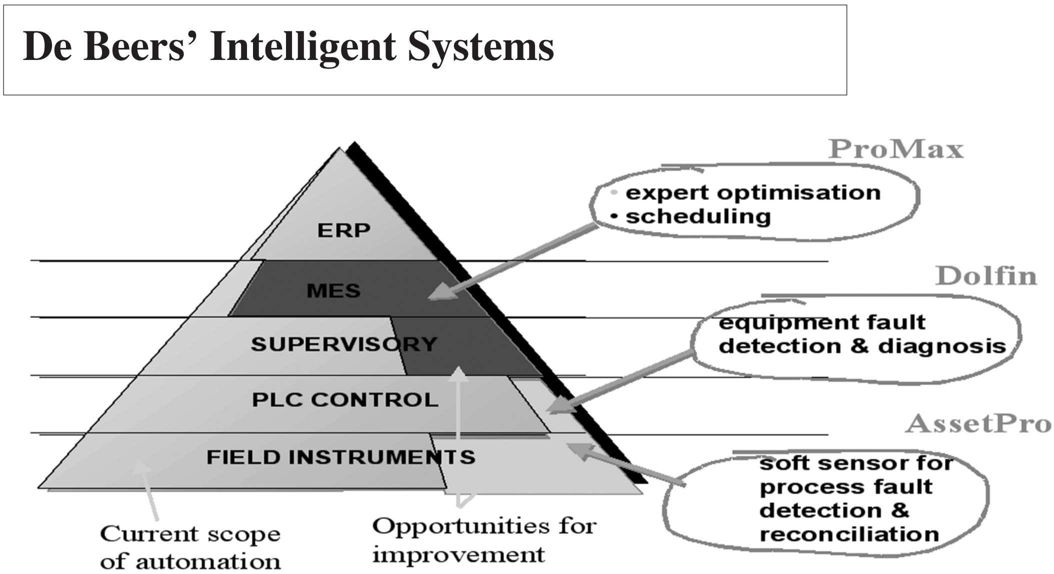

Figure 2—Position of soft sensor in the existing intelligent systems developed by DebTech, De Beers

reason that a soft sensor or a software sensor is called neural analyser. Because a soft sensor can replace a hardware analyser, it is also sometimes termed a virtual analyser[1,2].

Since its first appearance in the early 1990s, neural network predictive models and soft sensors have become a popular technique with more than 1000 applications in the process industries worldwide, such as in the petrol/chemical processes, mineral processing, metallurgy processes, and others[3–6]. In 2001, Dave Harrold called a soft sensor the 'process control's latest tool' in Control Engineering Europe[7].

Weightometer soft sensor

Since 1996, several intelligent systems have been developed and deployed at some mines among De Beers group, such as ProMax (a plant expert control system), DOLFIN (a diagnostic system for an X-ray diamond sorting machine), and Diamond Wizard (a diamond plant simulation). In order to make those intelligent systems work properly, one of the critical issues is to get accurate and reliable readings from online measurements, like weightometers to measure tph of ore/concentrate processed at the plants, as shown in Figure 2.

A soft sensor could potentially be used to enhance weightometer performance, based on the concerns of the following issues:

- Online weightometers are expensive
- On-going maintenance is often a significant concern
- Accuracy
- Reliability
- Needs for intelligent process control.

A prototype weightometer soft sensor (WSS) has been under research and development by the automation research group at DebTech, the technology centre of De Beers. The WSS forms part of the product called AssetPro, with its focus on assets improvement. The WSS consists of the main functions:

- ➤ online data source
- ➤ data validation
- ➤ dynamic weightometer models
- ➤ online fault detection
- ➤ online alarming
- ➤ online weightometer reconciliation.

The data acquired from a real time datasource are checked and treated by an Input Validation Model (IVM), see Figure 3. Only good data will be sent as inputs to the weightometer model to calculate the ton per hour (tph) of ore/concentrate. The calculated tph will be compared with the tph of the weightometer reading. If the deviation between the calculated tph value and the weightometer reading is greater than a given tolerance, then an alarm will be generated. And at the same time the weightometer reading will be replaced by the calculated tph values, which will be sent to the database and used by the process control system and production reporting system.

Results and discussion

The dynamic models used in WSS are developed using statistics and artificial intelligent (AI) adaptive techniques, such as neural networks. A rule-based model is also included in the WSS, to detect weightometer failure. The rule-based model is built by using operational knowledge captured from plant experts. Real time data are acquired through an OPC (client-server) linked from the plant SCADA. Data were sampled at an interval of two seconds, including about 100 variables of both analogue and digital. The prototype weightometer soft sensor is developed, shown in Figure 4 using CSense, a software product from Crusader Systems (www.crusader.co.za).

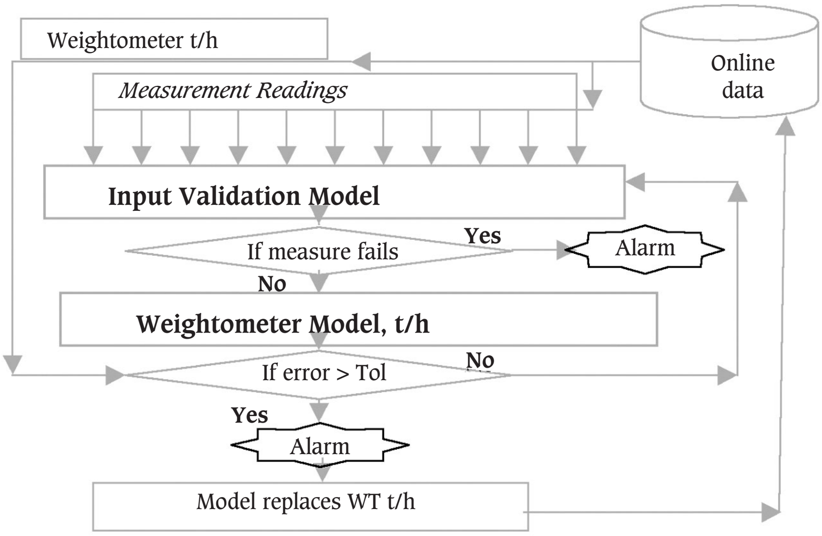

Figure 3—Main components of weightometer soft sensor, including online data source, input validation, dynamic model, fault detection, and data reconciliation

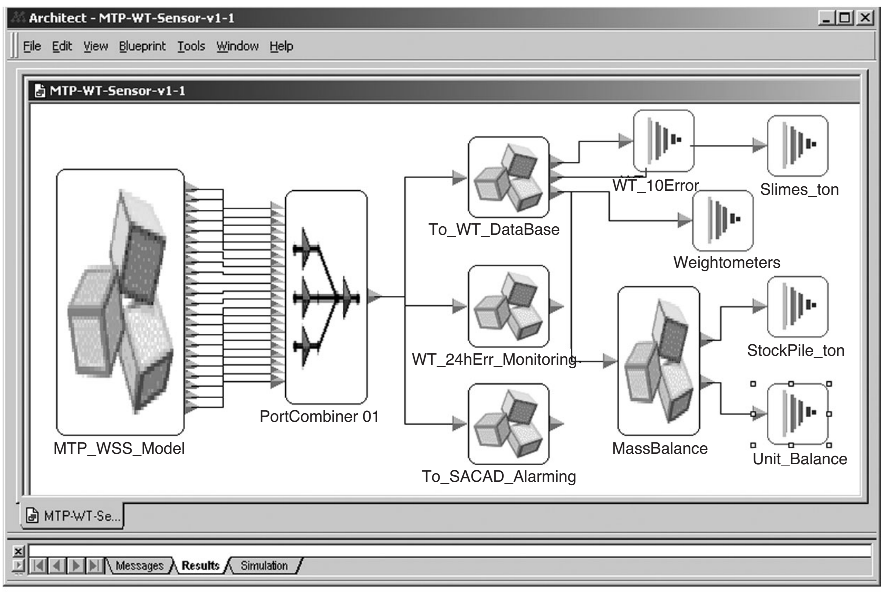

Figure 4—Prototype weightometer soft sensor developed using CSense, including WSS model, weightometer data reconciliation, deviation monitoring, alarming and mass balance calculation using validated values of ore/concentrate flow rate

Thirty-one dynamic neural net models have been developed for 31 individual weightometers for Venetia Mine. Among them, 28 models are evaluated in detail. The inputs used for each model vary with the measurements available, such as particle size distribution of ore/concentrate stream, running status, electric current or power drawn of the equipment associated with the weightometer we try to model. The equipment includes crushers, screens, scrubbers, conveyors, pumps, DMS cyclones, and others.

Most models have good correlation and are completed with a trained R^2 of more than 0.90 (see Table I), resulting in the calculation of the tph value within a daily error of < 4%, with confidence of > 90%. Those models with $R^2 \geq 0.85$ can have a daily error of 8% or less. Models with R^2 less than 0.85 are expected to improve, when adding one or more additional measurements. The required measurements are recommended for each individual weightometer, such as ore particle size, electric power or current of relevant equipment, etc.

The quality and quantity of data used to train the models are critical. The rule of 'garbage in and garbage out' applies. The majority of efforts (more than 85%) is spent on the acquisition of enough good data. The concerns and methodology of data collection and analysis will be discussed later in detail.

Even though the project is still under development, the good models, indicated by OK in Table I, form a complete set of soft sensors for all the weightometers used in the plant section from primary crushing to the stock piles of dense medium separation (DMS). The unit processes covered by soft sensors includes primary crusher, main stock pile, primary scrubber and screen, secondary crusher, re-crusher, secondary scrubber and screen, and DMS coarse stock pile, DMS fines stock pile and re-crushing stock pile. By collecting more good data, the models with R^2 less than 0.85 might be improved and used for the soft sensors, such as the weightometers numbered 24–27 in Table I.

As an example, Figure 5 illustrates two weightometer readings (tph) vs. model calculations, with daily error of 1% and 3% at a flowrate range of 230 tph and 980 tph respectively.

Major challenges to develop WSS

The most critical task is to develop 'good' neural net models, which must be accurate and robust enough to be able to model operational changes over a wide range. The accuracy of the models is the most important factor and it is sometimes necessary to trade off with robustness. The following method was used to develop and evaluate models[5–7]:

- data collection
- data preprocessing
- variable selection and time delay analysis
- neural network model training
- model verification.

- *Data collection*—Process analysis and data collection are essential since quality data are the only base on which to build good neural network models for weightometers. It is often found that not enough measurements are available to choose from to be able select the quality inputs, which cover a good correlation to the output of a weightometer reading. Too often, a first-time modeller believes that one can 'feed' the analysis software with mountains of historical data, then let it figure out what are important inputs. Even though some software packages can do

Table I

Models developed for weightometer soft sensor project

Version	MTP-WSS-V1-1-01				
No	Model	R^2	Status	Data set	Note
1	PC1-WT-042	0.97	OK	(Data set 15 May–15 July)	
2	PS1-WID-003	0.89	OK	(Data set 24 Apr–10 May)	Measure PS1-IT-01
3	PS2-WID-003	0.88	OK	(Data set 24 Apr– 10 May)	Measure PS2-IT-01
4	SC0-WT-001	0.98	OK	(Data set 26 June–21 August)	PS1-size critical
5	CS1-WT-001	0.91	OK	(Data set 26 June–21 August)	PS1-size critical
6	FS1-WT-001	calcu	OK	(Data set 26 June–21 August)	PS1-size critical
7	FS1-WT-005	0.96	OK	(Data set 18 June–15 July)	
8	CS1-WT-004	calcu	OK	(Data set 24 Apr–10 May)	Measure CS1_IT-01
9	SS0-WT-003	0.86	OK	(Data set 24 APR–10 MAY)	Measure SS0-IT-01
10	SC0-WTC-002	0.87	OK	(Data set 24 Apr–10 May)	
11	CS1-WTC-002	0.87	OK	(Data set 24 Apr–10 May)	
12	FS1-WTC-002	0.87	OK	(Data set 24 Apr–10 May)	
13	SC0_WT_003	calcu	OK	(Data set 24 Apr–10 May)	Measure SC0-IT-02
14	SC1-WT-004	0.92	OK	(Data set 14 May–24 May)	
15	SC2-WT-004	0.96	OK	(Data set 14 May–24 May)	
16	SC3-WT-004	0.91	OK	(Data set 14 May–24 May)	
17	RC0-WT-014	0.99	OK	(Data set 14 May–1 June)	
18	RC3-WT-004	0.99	OK	(Data set 21 June–24 June)	
19	RC4-WT-004	0.95	OK	(Data set 21 June–24 June)	
20	RC5-WT-004	x	x	Not enough data, it is hardly used	
21	RC6-WT-004	x	x	not used	
22	DC0-WT-001	0.35	bad	add more measurement	Measure DC0-IT-01
23	DF0-WT-001	0.27	bad	add more measurement	Measure DF0-IT-01
24	DC1-WT-002	0.71	bad	15 May–15 July, 30% data bad	look promising with more data
25	DC2-WT-002	0.71	bad	15 May–15 July, 30% data bad	look promising with more data
26	DF1-WT-002	0.15	bad	15 May–15 July, 50% data bad	look promising with more data
27	DF2-WT-002	0.59	bad	15 May–15 July, 30% data bad	look promising with more data
28	DT2-WT-001	0.15	bad	add more measurement	Measure DT2-IT-02

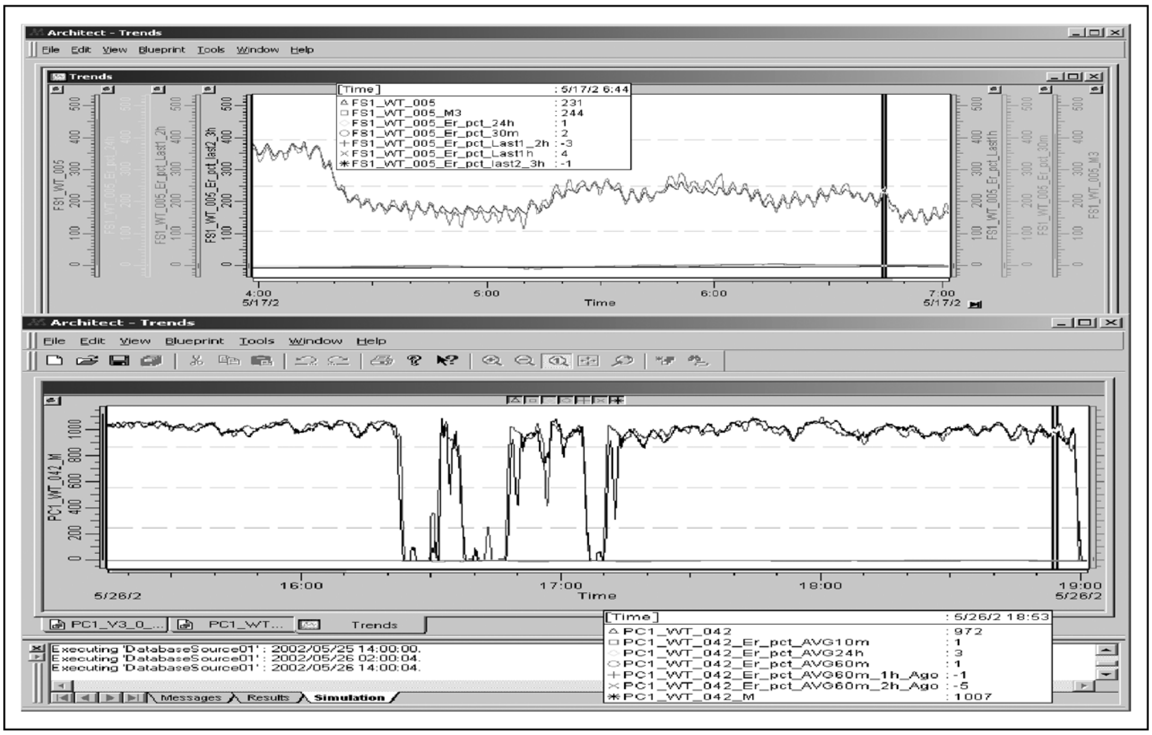

Figure 5—Weightometer readings against modelled ore/concentrate flow rate in tph, (daily average error of 1% and 3% within flowrate of 230 tph and 980 tph respectively)

such work by using techniques such as sensitivity analysis, in practice it is a bit more involved than that. Owing to time lags caused by different measurement, the exercise of data collection must be carried out simultaneously with the analysis of time delays. Sound knowledge of the processes can often help to find the correct variables and time delays.

➤ *Data preprocessing*—The main purpose here is to clean the data and prepare data for further process and analysis. Different tools use different techniques to do data preprocessing. The most common data analysis technique is to submit data to multiple passes of an algorithm designed to identify the most influential variables among the measurements available.
As data passed through the algorithm, the software identifies bad data, missing values, noise filtering, outlines and/or undesired data from different data sources. When evaluating soft sensor tools, pay special attention to preprocessing capabilities and the results produced.

➤ *Variable selection and time delay*—Variable and time delay selection is aimed at identifying the critical variables as inputs, which most influence the accuracy and robustness of the model to predict an output. But the problem is that one hardly knows in advance how much each input influences the predicted model output. A good toolkit permits setting a time delay range and includes algorithms to identify and test the sensitivity of each input variable to each output variable automatically.
Once the critical variables are identified, the next step is to approximate deadtimes and to do further evaluations on each variable's input to output. When an input at a given time delay contributes significant sensitivity in predicting the output, the input at that delay is important and should remain part of the model's input. Because of the co-relationship existing among all variables and time delay selection, it is important to note that each time when some variables are removed or time delay is changed, the evaluation and test should be repeated until the most influential input variables and corresponding delays are identified.

➤ *Model training*—The training process automatically adjusts the weighting factors in neural networks, based on well-conditioned training data. Neural networks tools sometimes tend to mislead modellers with high accuracy and the 'best-fit' solution, a phenomenon called over training. Such an over trained model has little robustness and loses its accuracy when it is fed with new data. To avoid over training, most software tools provide dynamic graphic presentations of modelling progress and allow the modeller to cancel training upon achieving an acceptable best-fit solution.

➤ *Model verification*—By using a completely different data set, which is not used to train the model, the trained model can be tested in its ability to predict the output. A good model will be able to predict the output accurately. A less than satisfactory verification result may require a close examination of each previous development step. At worst, it might require starting the model development process over, beginning with data collection.

Benefits

Even though the WSS prototype has shown overall satisfactory results in terms of accuracy of > 92% and good robustness, it has not yet been fully tested at the plant.

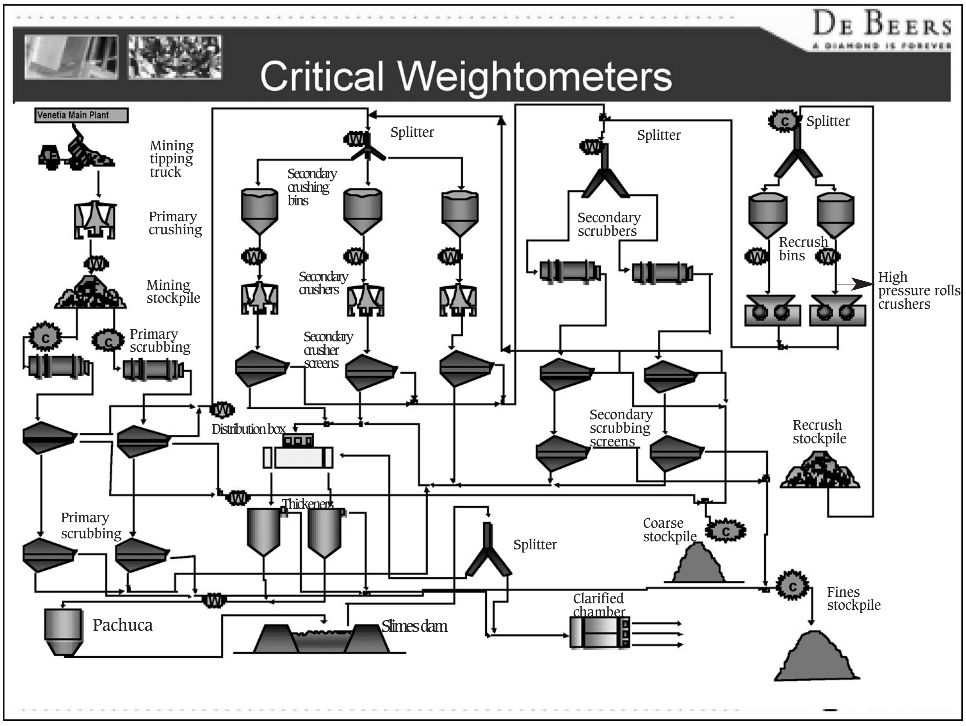

Figure 6—Some critical weightometers identified for a diamond processing plant, indicated by 'C'

Therefore the potential benefits from the system are included as part of the key performance indicators (KPI). The plant test was conducted in October 2002.

The main attractions of deploying weightometer soft sensor in diamond processes, compared with a hardware unit, can be summarized as follows:

➤ Reduce plant downtime
➤ Release weightometer maintenance pressure
➤ Replace non-critical weightometers.

It was identified that the number of weightometers could potentially be reduced from 31 to 8 critical ones at the main treatment plant of Venetia Mine. Figure 6 illustrates five critical weightometers indicated by 'C'. Among the non-critical weightometers, 11 are of concerning nuclear type, which have been subject to SHE.

Conclusions

A prototype weightometer soft sensor is under development at DebTech, De Beers in partnership with Venetia Mine. The main functions of the soft sensor system consist of (1) online data source, such as SCADA; (2) data validation; (3) dynamic weightometer models developed using neural networks; (4) online detection of weightometer failure; and (5) alarming and replacing of weightometer readings when the field unit fails. Some practical issues and concerns regarding model development were discussed, including data collection, data analysis, data preprocessing, variable selection, time delay, model training and model validation.

Thirty-one dynamic models have been developed and 28 of them are selected to evaluate in detail. All models with $R^2 \geq 85\%$ are accepted as good models and they can generally have satisfactory results with daily error less than 8% within a 90% confidence level. By using the good models, a set of soft sensors can cover all weightometers in the entire process starting from primary crusher to DMS stock piles. With more good quality data, the models for the weightometers in the DMS unit could be improved to good models. Furthermore, additional measurements are recommended for some individual weightometers.

The prototype is still under development at the time of writing. Therefore a final evaluation and report are not yet available. By deploying the weightometer soft sensor system, the potential benefits could include curtailment of plant downtime; reduction of maintenance loading and pressure and even replacement of non-critical weightometers, particularly where nuclear type weightometers are used.

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