A Decision Support System to Aid Quality Control in Iron Ore Production

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Abstract The quality of exported iron ore depends upon homogeneity of composition. This requires successive shipments be as uniform as possible in their content of each of several elements. Iron ore production can be represented as a series of loosely coupled sub-systems. For each sub-system, operational decisions are made to enhance the ore's uniformity of composition. At each mine, the Production Controller decides which blocks of ore should be mined. Train loads are despatched to the port, with the Quality Controller selecting the sequence from each of several mine sources. At the port, arriving train loads are stacked to a stockpile, chosen from possibly multiple current stockpiles. Finally, ships are loaded with ore, which may be reclaimed from one or more completed stockpiles. If the sub-systems are too tightly coupled, "hunting", or over-compensation, can occur. Attempts to control variability in composition can then actually cause variations of uncontrolled and increasing amplitude. The system becomes more manageable if the sub-systems' operations are decoupled, although tight informational coupling is still required. Simulation modelling has shown how the performance of the Production Controller and the Quality Controller can be enhanced if they aim to minimise the variability of their exponentially smoothed output, while basing their choices upon exponentially smoothed estimates of potential inputs. We discuss the operational system developed and evaluated using the simulation model. The Production and Train Control procedures that are needed to implement the operational system are data intensive. This leads to dangers of operator confusion, problems of transferability between operators, and the likelihood of error. We describe the development of spreadsheet-based decision support models to automate the system implementation, providing each controller with recommendations for their sequence of ore sources. The decision support models have been in operation for some months, and the experience of their problems and virtues is discussed.

Acknowledgement We thank Mr D.J. Miller for his encouragement, and BHP Iron Ore Pty Ltd for permission to publish this material.

1. INTRODUCTION

Iron ore provides a major export from Western Australia. Several companies produce the ore at inland mines and transport it by rail to ports on the west coast, where it is stored in stockpiles and finally shipped to overseas customers, who use the ore as feed for blast furnaces and sinter plants.

The major measure of product quality is uniform composition, not just in the ore's iron content, but in each of several other elements, including phosphorus, silica and alumina. For each of these components there is a target percentage, and upper and lower control limits which the shipped ore should not transgress. Consistent and predictable composition from ship to ship greatly enhances blast furnace and sinter plant production, as these plants are tuned to a particular feed composition. Changes in composition of the iron ore feed potentially diminish their productivity. Until recently, the Japanese steel mills published a yearly report summarising the composition uniformity from suppliers worldwide [TEX, 1994]. This information is not currently published, but we can assume that it is still being collated by the major customers.

There is the potential to control composition variability at several points through the production system, based on assays of material samples.

At each mine, there may be a number of mine faces currently available for production. For each mine face, there will be exploration samples and more detailed assays of the material extracted from the regular pattern of blast drill holes. This information can be used to plan production from the various mine faces available so as to deliver material with a composition as uniform and predictable as possible.

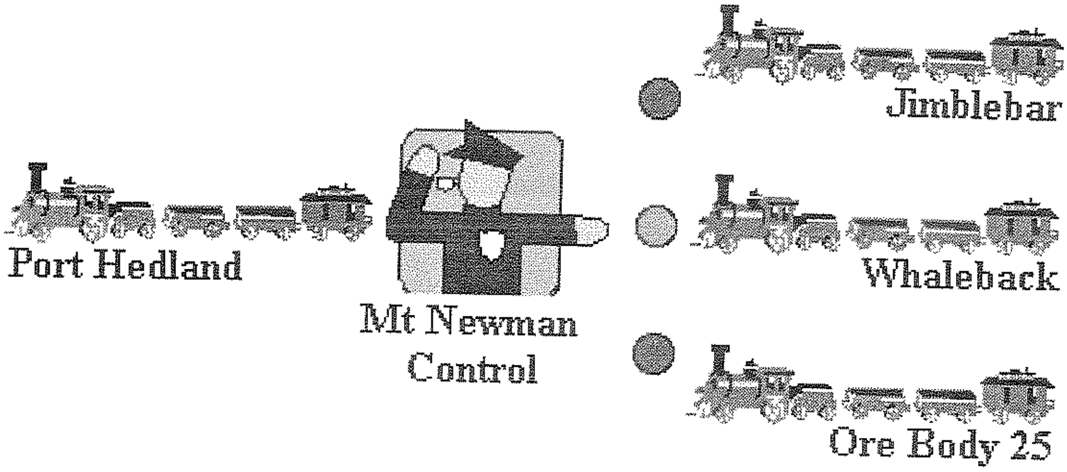

Figure 1: Quality Control at Mount Newman

A company may produce ore from several mines simultaneously which, once combined, form a single product for shipping. Train loads will be selected in sequence from the candidate mines. For example, BHP Iron Ore's major Whaleback mine is surrounded by other smaller ore bodies, which can also be mined. These satellite ore bodies are generally of lower grade than Whaleback, but can be used to extend the life of the Whaleback mine. Currently, two satellite mines, Jimblebar and Ore Body 25, are used to supplement the Whaleback product and are marketed as Newman product. Ore produced from each mine is crushed, assayed and loaded onto trains. Sequencing trains from these three mines provides opportunity to control the uniformity of grade. This train sequencing control is the major topic of the present study.

Once a train arrives at the port, it is unloaded and the ore is stacked on to a stockpile. More than one stockpile may be being built simultaneously, and an appropriate choice of candidate stockpiles can also be used to enhance the composition uniformity.

Finally, the stockpiled ore is reclaimed to load a ship. Since a number of completed stockpiles may be available for reclamation, the uniformity of composition may be further enhanced by the choice or mix of source stockpiles.

The application of intelligent stacking and reclaiming of ore at the port stockyard has been discussed previously by one of the present authors [Everett, 1996, 1997].

The work to be discussed here relates to the development and implementation of a decision support system to aid in the sequencing of trains from Mount Newman. As shown in Figure 1, the quality controller at Mount Newman has the task of selecting the sequence of trains to be dispatched from the three possible contributing mines. The ore from each mine is crushed, sampled and loaded on to a train. However, the composition of the ore available for train loading is available only after it has been crushed and assayed. Consequently, the sequencing decision has to be based on the past history of assays.

The development of the decision support system commenced with a simulation study, using the previous year's production data, to develop an exponential smoothing procedure to optimise the composition uniformity of ore delivered to the port. The results of this simulation study have been reported more fully elsewhere [Everett and Kamperman, 1999].

In the months before the simulation study was carried out, exponential smoothing and forecasting techniques had been adopted for the train selection procedure, with some noticeable increase in the composition uniformity of ore delivered to the port. The results of the simulation study enabled the train sequencing method to be further refined.

Applying the exponential smoothing and forecasting technique to train sequencing required the maintenance of continually updated smoothed compositions for each source of ore, and for the delivered ore. It was also necessary, before each train was dispatched (at four-hour intervals), to compute the forecast effects of each potential source, to decide which sources should be used to load the train. This procedure, carried out manually on a spreadsheet, was tedious, cumbersome and error-prone. Furthermore, the method required some skill and was difficult to pass on to new or untrained staff.

Accordingly a spreadsheet-based decision support model using Visual Basic macros [Microsoft, 1997] was developed to aid the train controller in his selection of train sequence from the three source mines.

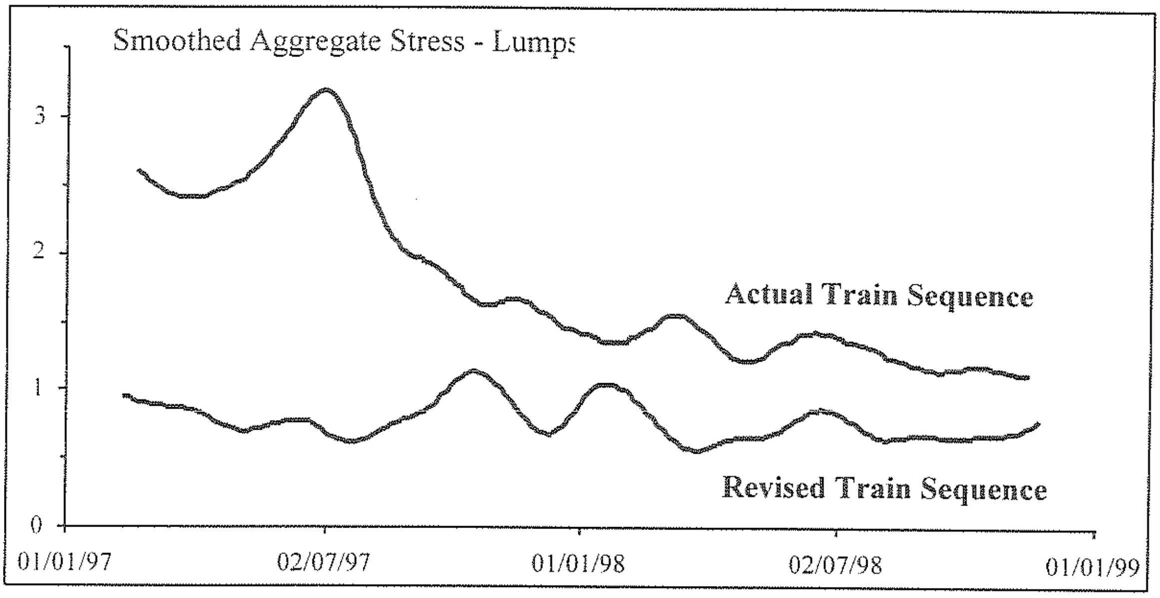

Figure 2: Potential and Actual Improvement in Overall Composition Control over Two Years

2. THE DECISION PROBLEM

Until early 1998, trains from Mount Newman were selected to try to make each "batch" of iron ore match the target composition. A batch equalled approximately half the capacity of a single port stockpile (for example, 150 kilotonnes), with the intention of creating uniform completed stockpiles through the control of two consecutive batches.

This approach requires very tight coupling between train control and the port stockpile control. For example, if a train is delayed, or a stockpile construction is altered, the train sequencing gets out of step with the designated stockpile build. Material designed for one stockpile is then inappropriate for the next stockpile. This leads to errors of over-compensation or "hunting". Replacing the batch target by a moving average target still generates hunting: an anomalous event causes discontinuity not only when it occurs but also when it falls off the end of the moving average.

Exponential smoothing was suggested both to forecast the incoming ore composition (since ore has to be consigned before its assays are available) and to provide a measure, which could be continually updated, of how well the composition target was being achieved. It was argued that an exponentially smoothed composition, with a half-life comparable to the stockpile capacity, would give more stable control than would a moving average or batch target.

A discussion of moving average, exponential smoothing and other forecasting techniques can be found, for example, in Newbold and Bos [1993].

3. THE SIMULATION STUDY

A simulation model was built using Extend [Diamond and Lamperti, 1997], to test and explore the use of exponential smoothing to sequence trains from the three mine sources. Because the elemental compositions show complex correlations and autocorrelations which cannot be reliably duplicated, the simulation model was designed to use the actual production over the preceding year and investigate the effect of changing the policies controlling the train sequence. This enabled the revised sequence resulting from any proposed policy to be compared with the performance of the actual train sequence.

The measure of performance was the root mean square aggregate stress for completed stockpiles. For each element, the stress was defined as the departure from target, divided by the permissible control interval. The aggregate stress is the square root of the sum of the squared component stresses [Everett, 1996].

The simulation model was designed to select each train from the three possible sources so as to minimise the forecast exponentially smoothed aggregate stress of railed ore. The composition of each potential source train was estimated as the exponentially smoothed composition of previous trains from that source. Performance was optimal with an alpha value of about 0.01 per thousand tonnes for each of the four exponential smoothings, but was not very sensitive to doubling or halving the value of alpha [Everett and Kamperman, 1999].

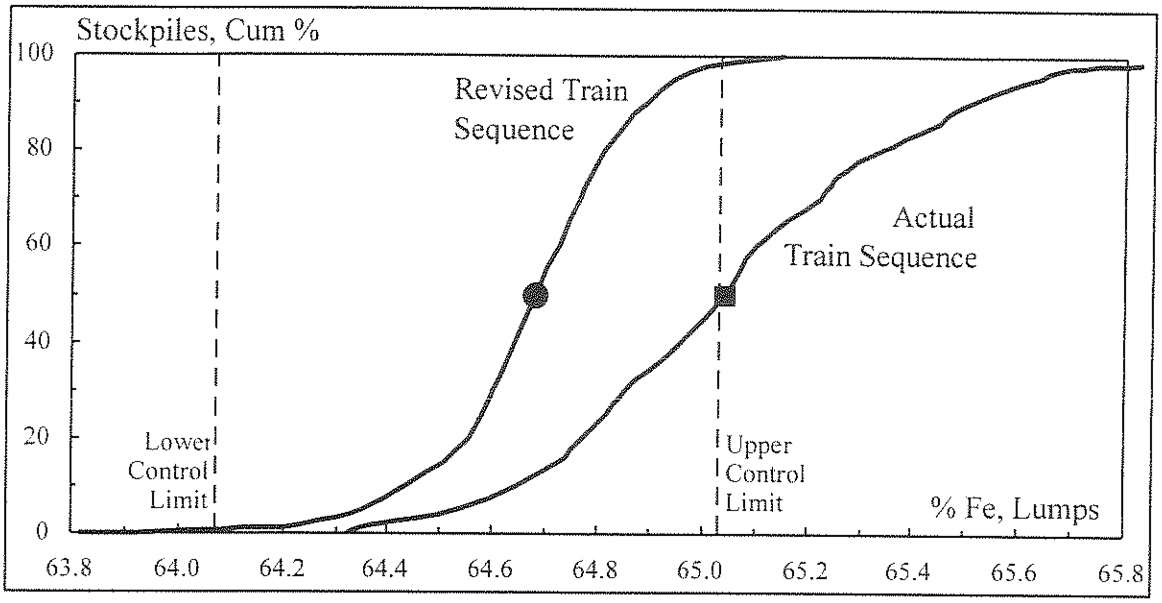

Figure 3: Potential Improvement in Fe Control

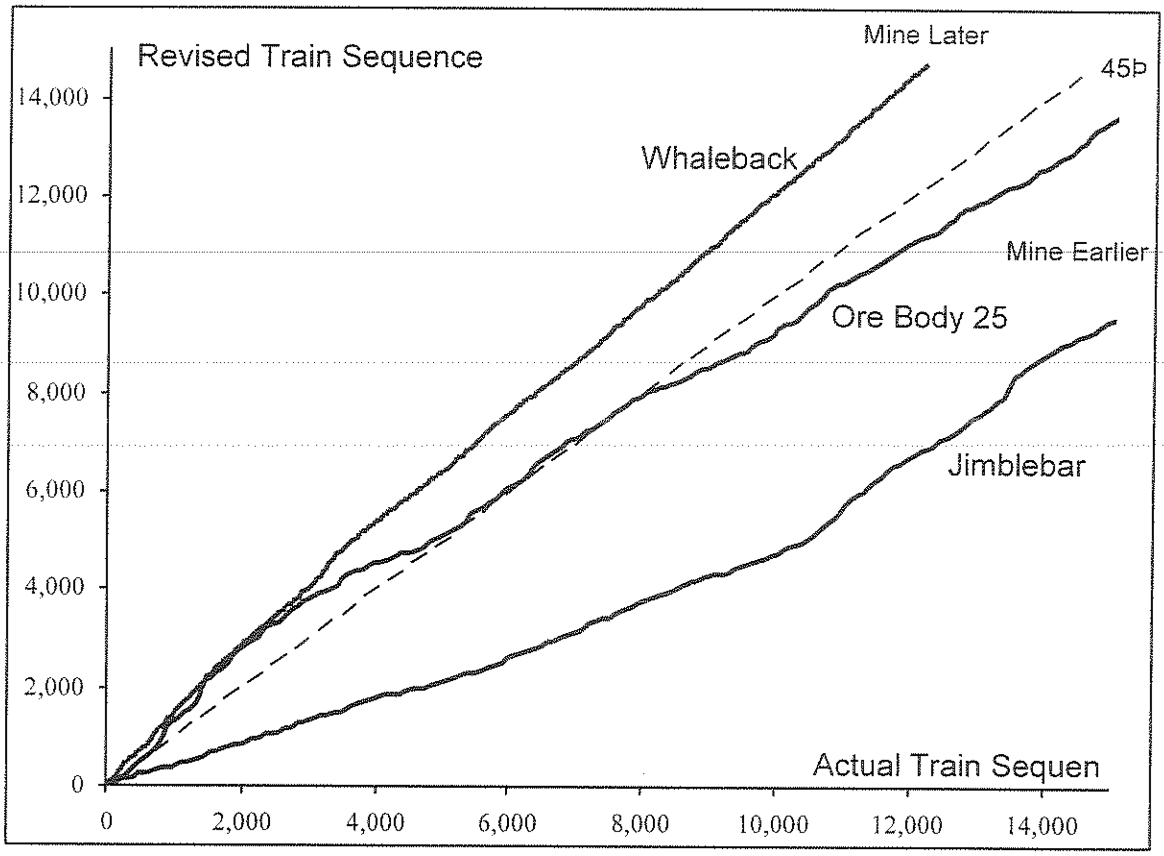

Figure 4: Potential Extension of Whaleback Mine Life by Increased Use of Low-Grade Satellite Mines

Revised production above the 45° line represents production later than actual.
Revised production below the 45° line represents production earlier than actual.

Update **Reconcile**

Update Number:- 104
Trains Sent:- 24

Parameters:- **Updated:-** 24/12/98 12:41

Source:-	Alpha per kt	Wagons/Block	kt/Wagon (Average)	% Lump (Average)	Relative Importance of Lump Stress
Whaleback (W)	0.01	55	0.1122	52.4%	
Jimblebar (F)	0.01	55	0.1068	57.0%	0.50
Ore Body 25 (X)	0.01	55	0.1092	52.1%	
Output Trains	0.01				

		Lump	Lump Composition				Fine	Fine Composition			
		kt	Fe	P	SiO2	Al2O3	kt	Fe	P	SiO2	Al2O3
Target			64.55	0.056	3.40	1.62		63.30	0.068	4.10	2.40
Unit Stress			0.48	0.006	0.45	0.13		0.75	0.006	0.39	0.30
Feasible Range:-	Stress										
Maximum	+30	20.0	78.95	0.236	16.90	5.52	20.0	85.80	0.248	15.80	11.40
Minimum	-15	0.0	57.35	0.000	0.00	0.00	0.0	52.05	0.000	0.00	0.00

Recommended Selection for Next Train Blocks:-

	Recommended Choice for Next Train Blocks				Train kt			Cumulative Blocks			Cumulative kt		
Train Block					W	F	X	W	F	X	W	F	X
1 to 4	X	F	W	W	12.3	5.9	6.0	2	1	1	12.3	5.9	6.0
5 to 8	X	W	F	W	12.3	5.9	6.0	4	2	2	24.7	11.7	12.0
9 to 12	X	W	F	W	12.3	5.9	6.0	6	3	3	37.0	17.6	18.0
13 to 16	W	F	W	X	12.3	5.9	6.0	8	4	4	49.4	23.5	24.0
17 to 20	W	F	W	W	18.5	5.9	0.0	11	5	4	67.9	29.4	24.0
21 to 24	X	W	F	W	12.3	5.9	6.0	13	6	5	80.2	35.2	30.0

Last Update:-

	Trains	Lump	Lump Composition				Fine	Fine Composition			
Source:-	Sent	kt	Fe	P	SiO2	Al2O3	kt	Fe	P	SiO2	Al2O3
Whaleback (W)	14	41.7	66.00	0.048	3.10	1.16	46.6	65.58	0.057	2.71	1.70
Jimblebar (F)	5	15.3	62.21	0.046	5.43	2.70	9.6	60.20	0.056	6.82	3.86
Ore Body 25 (X)	5	14.1	62.09	0.090	4.73	1.88	15.6	60.85	0.093	5.69	2.65
Output Trains	24	71.1	64.41	0.056	3.92	1.63	71.8	63.83	0.065	3.91	2.20

Last Smoothing

	Alpha		Lump (Smoothed)					Fine (Smoothed)			
Source:-	per kt		Fe	P	SiO2	Al2O3		Fe	P	SiO2	Al2O3
Whaleback (W)	0.01		66.14	0.050	2.81	1.18		65.37	0.059	2.85	1.83
Jimblebar (F)	0.01		62.43	0.050	4.78	2.51		61.65	0.057	5.48	3.23
Ore Body 25 (X)	0.01		62.23	0.097	4.28	1.95		61.14	0.100	5.28	2.72
Output Trains	0.01		64.49	0.057	3.71	1.62		63.83	0.066	3.89	2.23

Control / OldTrains / NewTrains / LogUpdate / LogSmooth / Graph / PortTrains

Figure 5: The Decision Support Model - A Macro-Operated Spreadsheet

4. POTENTIAL SYSTEM PERFORMANCE

Figure 2 shows how actual performance improved over the two years, thanks to the introduction of exponential smoothing in early 1998. But a revised train sequence, based on optimal exponential smoothing, would give still better performance. The conclusion is confirmed by Figure 3, showing the revised train sequence would better control the iron variability. Actual departures from target were predominantly above the upper limit for iron (and therefore below target for the other elements). Excessive iron content would have caused less complaint from customers, but represents a loss to the producer. This loss is apparent in Figure 4, which shows that the revised sequence would have included more low-grade satellite ore, considerably extending the life of the main Whaleback mine.

ARIMA analysis [SPSS, 1988] of each set of source data was used to find if a more sophisticated forecasting system would have better forecast the source assays (which, as we have seen, are not available at the time of decision). An ARIMA(101) model is the best forecaster. Even for simple exponential forecasting, the best alpha was 0.42, considerably greater than the alpha of 0.01 found to optimise the simulation. The simulation was re-run, basing train sequencing on actual train assays (which in reality would not yet be available). Paradoxically, this gave considerably worse performance than exponential smoothing with the low 0.01 alpha value. The reason for this paradox is that a "bad" train can block the use of "good" trains that follow it. So decisions based on a heavily smoothed source composition give better performance than if the best forecast or even the true values were used.

5. THE DECISION SUPPORT MODEL

The decision support system (DSS), developed through the simulation study, was adopted for train control at Mount Newman. As assay values became available, it required exponentially smoothed values be updated for each element component of each mine source, and of the dispatched train sequence. The system also required the effect of each potential source on the exponentially smoothed dispatched composition be evaluated and compared before each train was selected. The procedure was done manually on a spreadsheet, but proved quite tedious. Train selection is done at four-hour intervals night and day. An operator could easily make errors or become confused. It was also difficult to explain the system to new or untrained personnel. But operators were familiar with using Excel spreadsheets; data sources came through this medium, and the software was available on every desktop computer. So it was desired to have an Excel-based DSS model.

A spreadsheet workbook (Figure 5) was designed, including Visual Basic macros, to implement the DSS. The model is driven by two macro buttons "Update" and "Reconcile". As dispatched trains assay data become available, they are pasted in the "New Trains" sheet. The "Update" button causes the new data to be transferred to the "Old Trains" sheet, and updates the smoothed source and dispatched compositions. New recommended choices for the next six trains are automatically reported (each train consists of four 55-wagon blocks, and each block is selected from the three possible sources). The smoothed values for the mine sources and the dispatched ore are plotted in the "Graph" sheet. When trains arrive at the port they are unloaded and assayed again. These data are pasted into the "Port Trains" sheet. The "Reconcile" button causes them to matched to the "Old Trains" and transferred to a reconciliation workbook where the cumulative assays are plotted, to compare the port and mine data.

6. DISCUSSION AND CONCLUSIONS

The decision support system whose development and implementation has been described here, has been in use at Mount Newman for some months. It saves considerable labour, and provides information which previously was not so readily accessible. The system's performance will continue to be evaluated.

The system not only generates less variable iron ore, but also permits the use of a higher proportion of low grade ore from satellite mines. This suggests the economic life of the Whaleback mine can be increased by about twenty percent, a valuable bonus to the study.

The DSS is transferable to other stages in the iron ore production system, and to other extractive systems (such as coal or oil shale production). A variant of the DSS has already been implemented at another BHP iron ore mine, to control the sequencing of ore extraction from the multiple available mine faces.

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