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Application of geostatistics to construct a coal quality model

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ABSTRACT

Coal washability data can be used for assessing coal quality. However, the techniques of using these data to solve quality problems differ from one mine to another and certain problems may never really be investigated due to limitations of the available techniques. One promising way to overcome these limitations is by correct application of geostatistics.

A geostatistical study on coal washability data was undertaken based on a data set of closely spaced in-pit bore cores. These bore cores were analysed consistently over a relatively simple geological area. The average distance between the drill holes was about 100 m. There were 78 drill holes available for the area after deleting the erroneous bore cores. During the study, nine extra closely spaced drill holes were drilled within a single mining block.

A procedure to construct two coal quality models, a kriging or cokriging model and a simulation model, was proposed. The modelling results for the data above are discussed and results of a mine scheduling exercise based on the models developed are included.

INTRODUCTION

This paper presents a geostatistical evaluation of in-situ coal quality from laboratory determined coal washability data. The study was based on coal quality data from a geologically simple area which was closely drilled and analysed.

Washability data were obtained from laboratory testing undertaken according to Australian Standard AS 1661 (1979) procedures. During the test, coal was placed in a liquid of pre-determined density. The material which floated was first dried and weighed, and heat-treated under specific conditions to determine the percentage ash. This gave the percentage of material floating and the ash content for a series of densities. These results were then presented in the form of tables, curves or mathematical functions. There are usually some correlation relations between the floats (yields) and ash at different densities. The sum of the floats percentages at all separate densities and the sink should be equal to 100.

Coal washability data are essential for planning and design in most coal mining activities. These include deposit evaluation at the development stage, mine planning and scheduling, coal preparation plant design and operation. To make full use of these data is of primary importance especially when coal markets are becoming increasingly competitive. Geostatistics has found a place in the mining industry where it is regarded as a very promising tool to deal with industry problems. In the past, most geostatistically successful applications were based on studying single variables such as the coal thickness, raw coal ash, and cumulative coal yield with corresponding ash content at certain separating densities (Armstrong, 1984). No coal washing plant can achieve perfect separation and many mining activities need more than a single value evaluation. For prediction of plant yield and scheduling of mining production either a plant simulation model based on various partition curves or the simpler general partition curve for the plant is usually used.

In this study, methods using geostatistical techniques were investigated to construct two types of models for in-situ coal quality based on coal washability data. The first, the prediction model, is constructed either by kriging or cokriging to ascertain the best possible assessment of in-situ coal quality (Wu, 1990 and Just, Wu and Gillies, 1990). The other, the simulation model, is constructed by use of conditional simulation techniques and has the following properties.

1. A coal quality data set is established for a predefined support level such as small blocks which correspond to hourly production across the deposit.
2. The variables of interest, such as coal yield, are set within the same distribution (histogram) and the same variation (variogram) as the sample data.
3. The simulated values at sampled points coincide with real values, that is the simulated grades have the same values as the real grades at the sample points.

   This enables problems such as plant feed fluctuation to be visualised.

The two models form the basis for mine and plant optimisation (Just, Wu and Gillies, 1990). A study has been undertaken using data from a Central Queensland coal deposit to illustrate these concepts.

DATA USED IN THE STUDY

The data available were the in-pit bore cores from the mined out area in a large steaming coal mine. This set covered an extensive area from a number of mining pits. For the purpose of this study, only the data in a 'homogeneous' and geologically simple area has been used.

The data selected were from in-pit 100 mm diameter bore cores located in a 3 m uniform thickness seam. In general, these bore cores were taken in each strip (70 m width) at an interval of approximately 100 m. They were analysed by float and sink testing for eight separating densities from 1.35 to 2.10 g/cm^3 across a size range of +0.5 mm to -50.0 mm. After deleting the erroneous bore cores, there were 78 drill holes available in the selected area. In order to estimate the variograms for distances less than 100 m, nine extra 100 mm diameter special purpose bore holes were put in a block of dimension 100 m x 70 m. This block area has the same dimensions as that used for both long- and short-term planning. These data enabled the study to be successfully carried out.

VARIABLES USED IN THE STUDY

One factor which had to be considered in the study was that the ash per cent, yield, and relative density washability data were correlated by a complex non-linear relationship. This introduced difficulties in the application of geostatistics and it meant that certain practical assumptions needed to be made in the study. If the density vs the cumulative yield curve for this density interval is approximated by a straight line (Wu, Gillies and Just, 1991) it has been shown that the incremental yield for a separating density interval is independent of the incremental ash per cent at that density interval. This makes it possible to study the yield variables and ash variables separately. Further investigation into the ash vs density relationship indicated that the instantaneous ash (the ash per cent of particles which have the same relative density as the separating density) vs relative density relationship was almost constant for a coal seam

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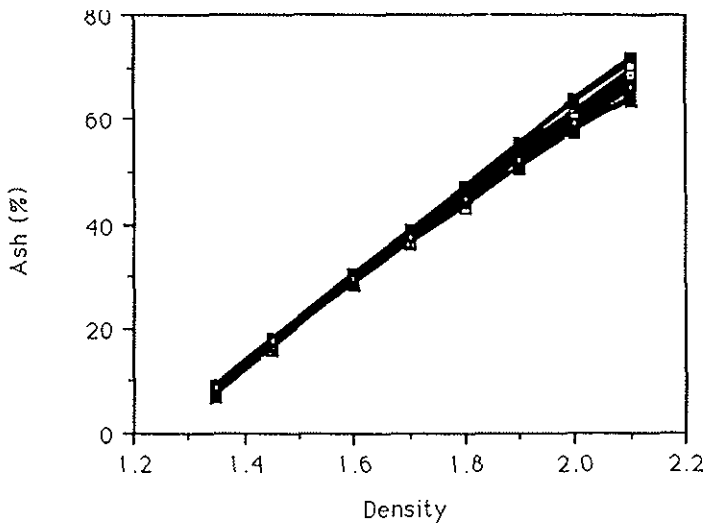
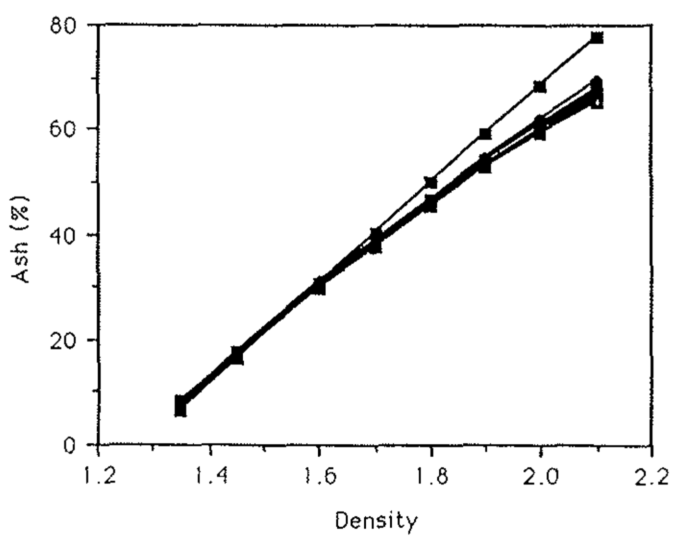


a) for the bore cores in one mining pit.



b) for the bore cores in specially drilled block.

FIG 1 - Instantaneous ash vs density curves.

over a certain mining area. This was also indicated by Ilievski (1987).

Figure 1 shows these curves for both the bore cores in one mining pit area and for the nine bore cores drilled specially in the 70 m x 100 m block. Figure 2 presents the average curves for the two corresponding data sets. These curves overlay each other. It can be seen that fluctuations in curves (Figure 1) are mainly due to analysis errors. The relatively constant relationship makes it necessary to geostatistically study only the yield variables.

For the study of yield information, there are two options available. One is to study the incremental yields at different densities and the other is to study the cumulative yields at different densities and then convert them to the incremental yields to obtain the coal washability data. The first option is normally selected if variograms are well defined since this avoids subsequent calculations. However, if the intrinsic variogram model can be fitted for the cumulative yields at different densities but not for the corresponding incremental variables, the later option should be used. In this study, the former was selected for further study. There were a total of nine variables (eight yields and one sink). These were denoted by y135, y145, y160, y170, y180, y190, y200, y210, and yss2.

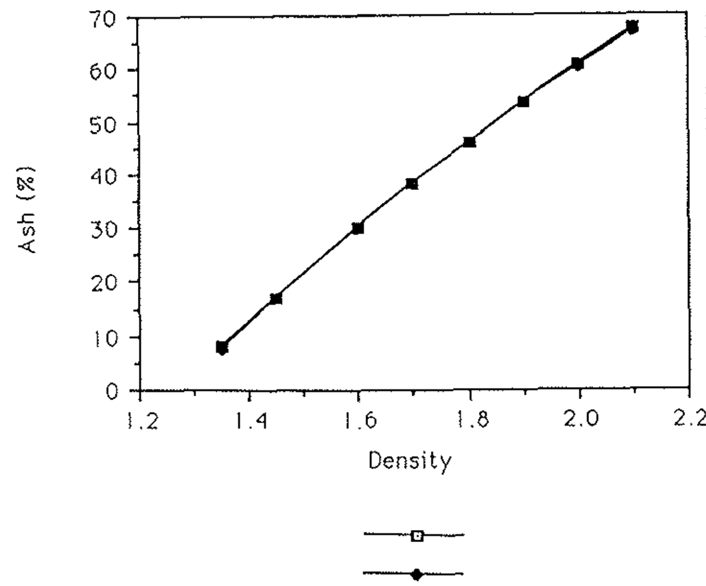


FIG 2 - Instantaneous ash vs density curves for the average values for the pit and block in Figure 1.

BASIC STATISTICS AND VARIOGRAM ANALYSIS

Statistical results

The mean, variance and correlation coefficients for the incremental yields for the nine float and sink fractions were calculated. The results showed that most of the mass was in y135, y145 and y160 with much less at y180, y190, y200 and y210. Some of the correlation coefficients between the yields are very significant. Table 1 lists the correlations for the yields. The histograms were well defined and symmetrically shaped except that for y210.

TABLE 1

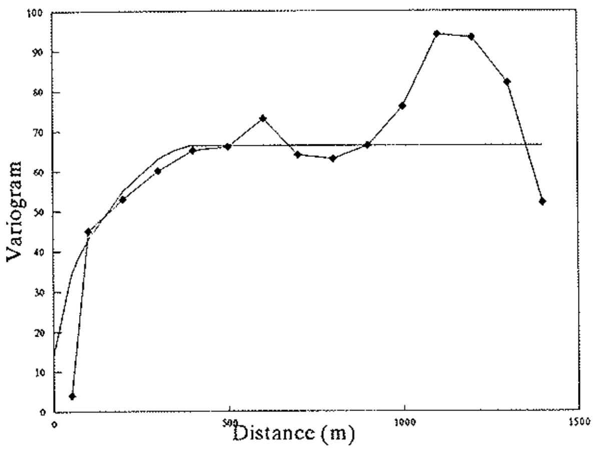
Correlation coefficients for the yields and sink.

	y135	y145	y160	y170	y180	y190	y200	y210
y135	1.000							
y145	-0.750	1.000						
y160	-0.671	0.153	1.000					
y170	-0.441	0.012	0.436	1.000				
y180	-0.399	0.034	0.316	0.328	1.000			
y190	-0.289	0.114	0.078	0.023	0.215	1.000		
y200	-0.119	-0.082	0.086	0.037	0.090	0.274	1.000	
y210	-0.286	0.002	0.216	0.226	0.289	0.261	0.585	1.000
yss2	-0.245	0.148	-0.020	-0.027	-0.002	0.133	0.059	0.017

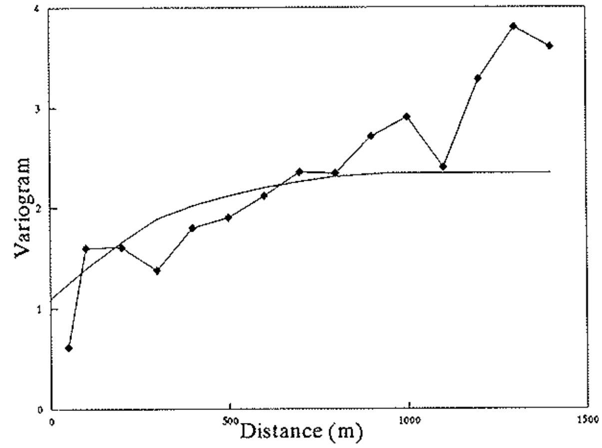
Variogram analysis

After some anisotropic tests, omnidirectional variograms were chosen as the variograms for further study (the deposit was characterised by isotropic behaviour). The variograms were calculated based on 79 samples, that is, only one sample from the closely drilled samples was included. This was done because if all the nine closely drilled samples were included in the variogram calculations, the variances or in this case the sills of the variograms

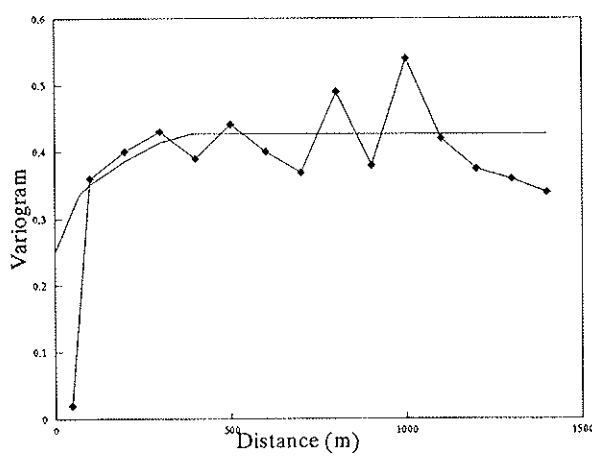
FIG 3 - Typical experimental variograms and their theoretical models.



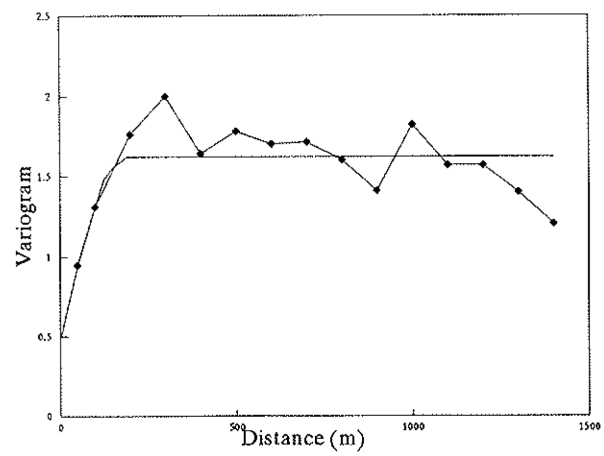
Y135:			
	Nugget.	14	
	Structure	sill	range
	spherical	14.37	70
	spherical	38	390



Y170:			
	Nugget.	1.1	
	Structure	sill	range
	spherical	0.5	390
	spherical	0.74	950



Y190:			
	Nugget.	0.25	
	Structure	sill	range
	spherical	0.06	70
	spherical	0.117	390



YSS2:			
	Nugget.	0.48	
	Structure	sill	range
	spherical	1.15	190

would not be correctly estimated. This process is known as declustering (David, 1989). However, in fitting the variogram models, the variogram values at distances of less than 100 m were needed to define nugget effects. Knowledge of the behaviour of the variograms at or near the origin is especially important for constructing the conditional simulation model. To meet these requirements, the variograms were calculated from 87 samples. Variogram values for distances less than 100 m were used to fit the variograms calculated for 79 samples. All the variograms calculated from the 79 samples and especially those corresponding to the large mass fractions of y135, y145 and y160 were well defined.

Fitting of the variograms were done visually through a graphics terminal and all were well fitted by nested spherical models. Nugget effects were fitted according to the variograms calculated from the 87 samples as outlined above. The experimental variograms together with the fitted models are listed in Figure 3.

The cross-variograms for the variables were also calculated. Some were extremely well defined. Figure 4 lists the cross variogram for y135 and y145 together with the fitted model.

Fitting the linear model of coregionalisation

In order to carry out the cokriging and co-simulation for the correlated variables, a model which fitted all the variograms and some of the cross-variograms was needed. The linear coregionalisation model which is commonly used as a model in geostatistics was selected.

The theoretical foundation for fitting a linear coregionalisation model is described in Journal and Huijbregts (1978). The basic concept is to decompose the correlated variables into a series of elementary independent variables. Subsequently, certain linear combinations of these variables produce the variograms (covariances) and cross-variograms (cross-covariances) of the

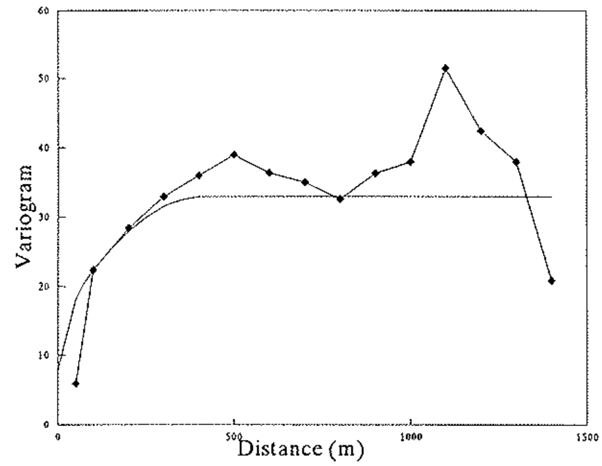


FIG 4 - The cross-variogram for y135 and y145 (cross-variogram value multiplied by -1).

correlated variables.

It is a relatively easy matter to fit the linear coregionalisation model to less than three correlated variables. As soon as more than three variables have to be considered, this becomes very difficult unless the so-called intrinsic model is valid where all the variograms and cross-variograms can be derived from a single structure by multiplying or dividing certain coefficients. In this study, the intrinsic models are not valid since the variograms have different ranges. A computer program was written and special procedures were defined to deal with this problem (Wu, 1990). The fitted linear coregionalisation model for the yield variable is listed below.

$$Y135 = 3.7417Y^1_0 + 3.7908Y^1_1 + 6.1644Y^1_2$$

$$Y145 = 1.959Y^1_0 + 1.8874Y^2_0 - 2.1737Y^1_1 + 1.9429Y^2_1 - 1.9564Y^1_2 + 3.0004Y^2_2$$

$$Y160 = 1.1225Y^1_0 - 1.1651Y^2_0 + 0.6185Y^3_0 - 1.6303Y^1_1 - 1.8239Y^2_1 + 0.1251Y^3_1 - 0.743Y^1_2 - 0.4844Y^2_2 + 1.0165Y^3_2$$

$$Y170 = 0.4624Y^1_0 - 0.4799Y^2_0 - 0.4627Y^3_0 + 0.6647Y^4_0 - 0.4948Y^1_2 - 0.3226Y^2_2 - 0.3039Y^3_2 + 0.2424Y^4_2 + 0.8602Y^1_3$$

$$Y180 = 0.3143Y^1_0 - 0.3262Y^2_0 - 0.4897Y^3_0 - 0.3888Y^4_0 + 0.1542Y^5_0 - 0.3374Y^1_2 - 0.22Y^2_2 + 0.0912Y^3_2 - 0.3721Y^4_2 + 0.0313Y^5_2 + 0.2151Y^1_3 + 0.6195Y^2_3$$

$$Y190 = 0.5Y^6_0 + 0.2449Y^4_1 + 0.3421Y^6_2$$

$$Y200 = 0.3464Y^7_0 + 0.1414Y^7_2 + 0.1581Y^3_3$$

$$Y210 = 0.1386Y^7_0 + 0.1918Y^8_0 + 0.251Y^5_1 + 0.181Y^3_3 + 0.0072Y^4_3$$

$$Yss2 = 0.6928Y^9_0 + 0.3391Y^9_9$$

where $Y^1_0, Y^2_0, \ldots, Y^9_0$ are independent elementary variables with no variogram structure; Y^1_1, Y^2_1, Y^3_1, Y^4_1, Y^5_1, are independent elementary variables with unit sph(70) variogram (spherical variogram with a range of 390 m and a sill of 1); Y^1_2, Y^2_2, Y^3_2, Y^4_2, Y^5_2, Y^6_2, Y^7_2 are the variables with unit sph(390) variogram (spherical variogram with a range of 390 m and a sill of 1); Y^1_3, Y^2_3, Y^3_3, Y^4_3 are the variables with unit sph(950) variogram; and Y^1_4 is the variable with unit sph(190) variogram.

KRIGING AND COKRIGING

After fitting the variogram models and the linear coregionalisation model, kriging and cokriging were carried out by using standard geostatistical software.

TABLE 2

Basic statistics for the kriging results.

variable	mean	variance
y13k	32.555	20.552
y14k	38.200	6.413
y16k	13.814	0.876
y17k	4.712	0.816
y18k	2.571	0.457
y19k	1.938	0.039
y20k	0.978	0.016
y21k	0.555	0.024
yssk	4.735	0.346

(a) means and variances

	y13k	y14k	y16k	y17k	y18k	y19k	y20	y21k
y13k	1.000							
y14k	-0.763	1.000						
y16k	-0.716	0.251	1.000					
y17k	-0.485	-0.056	0.528	1.000				
y18k	-0.640	0.155	0.593	0.754	1.000			
y19k	-0.667	0.429	0.341	0.391	0.654	1.000		
y20k	-0.519	-0.017	0.621	0.615	0.739	0.526	1.000	
y21k	-0.617	0.105	0.669	0.708	0.781	0.559	0.870	1.000
yssk	-0.231	0.166	-0.056	0.019	0.061	0.317	0.180	0.091

(b) correlation coefficients

The means and variances and the corresponding correlation coefficients for the kriging and cokriging results are listed in Tables 2 and 3. Table 4 lists the kriging and cokriging variances together with the improvements obtained by cokriging rather than kriging in terms of estimation variances. One of the concerns for (co)kriging the coal washability data is that the (co)kriged percentage yields and sink reactions will not sum to 100. This was checked for the kriging and cokriging results. Table 5 lists some statistics about these differences and the statistics for the absolute values of the differences. A quadratic programming approach was used to correct this difference. Adjustments of differences were very small and kriging and cokriging variances were corrected. Table 6 lists the modified kriging and cokriging results for the closely drilled blocks using the 79 data set together with the 'actual value' of the block obtained by taking the average of the nine drill confidence holes. Table 7 shows the 95 per cent confidence limit calculated from the (co)kriging variance assuming the normal distribution of the kriging error. Despite the arguments involved in this usage of the (co)kriging variance in general geostatistical applications, this is a proper usage for the majority of coal geostatistical applications. From these results, the following points can be drawn.

1. Both kriging and cokriging results reproduced most of the relationships between the yields at different densities. The

TABLE 3
Basic statistics for the cokriging results.

variable	mean	variance
y13k	32.592	17.894
y14k	38.197	6.389
y16k	13.805	0.867
y17k	4.704	0.764
y18k	2.568	0.450
y19k	1.938	0.039
y20k	0.980	0.018
y21k	0.556	0.021
yssk	4.735	0.346

(a) means and variances

	y13k	y14k	y16k	y17k	y18k	y19k	y20k	y21k
y13k	1.000							
y14k	-0.743	1.000						
y16k	-0.713	0.292	1.000					
y17k	-0.500	-0.042	0.476	1.000				
y18k	-0.687	0.176	0.664	0.748	1.000			
y19k	-0.742	0.426	0.463	0.446	0.688	1.000		
y20k	-0.541	0.000	0.691	0.640	0.763	0.529	1.000	
y21k	-0.601	0.078	0.718	0.695	0.776	0.562	0.910	1.000
yssk	-0.380	0.158	0.077	0.097	0.127	0.317	0.159	0.105

(b) correlation coefficients

TABLE 4
Kriging and cokriging variances and the gains from cokriging.

variable	average kri variance	average gain (%)	average cokri variance
y13k	12.567	11.010	12.39
y14k	5.592	5.590	0.04
y16k	2.104	2.016	4.18
y17k	0.294	0.255	13.16
y18k	0.173	0.165	4.62
y19k	0.063	0.063	0.00
y20k	0.017	0.017	0.00
y21k	0.024	0.024	0.00
yssk	0.385	0.385	0.00

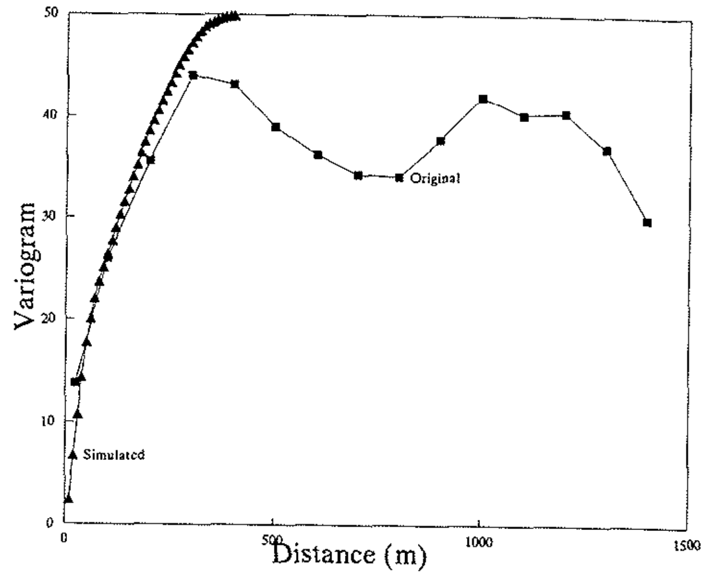


FIG 5 - Variogram for the values of the simulated small blocks and its original model for yield at 1.35.

statistics, means, variances, and correlation coefficients for the kriging values are very similar to those for the cokriging values.

2. The gain of cokriging over kriging in terms of the estimation variances is small. Even for the yield at 1.35 where the gain is the most, these gains are negligible. Kriging can be performed instead of cokriging if the cokriging gain can not be justified in terms of extra cost of this effort.
3. The problem of the estimated results for percentage yields for a block not summing to 100 exists both in kriging and cokriging and the scales of 'imperfection' are both very small.
4. The differences between the kriging results, modified kriging results, cokriging results and modified cokriging results are very similar compared with the differences between these results and the true block value.
5. Except for yield values at 1.80 (y180) the estimation errors are all within the 95 per cent confident intervals calculated from the kriging variance under the assumption of normally distributed estimation error. The results also imply that the kriging variances give a good indication of the uncertainty for the prediction in most separating densities.

It should be stressed that to use only the data from the mined out zone to predict the area to be mined is appropriate if the mean of the area to be mined is the same or similar to the area already being mined and there is no sudden change of the spatial variabilities. This may be verified by other information including non-quantitative information.

CONDITIONAL CO-SIMULATION

For development of the simulation model, the simple simulation approach corresponding to the kriging approach is not considered. This is because the independently simulated variables will not have the required correlations between the simulated variables because of the way they were created. As a consequence, only the co-simulation approach is used to construct the simulation model. Quadratic programming is again used to modify the original simulation results. The technique of correction of variances is introduced to make the final modified model 'perfect'. This approach is made up of the following main steps.

1. performing gaussian anamorphosis of the raw variables
2. fitting the linear coregionalisation model to the gaussian

TABLE 5

Statistics of the difference between 100 and the sum of kriged or cokriged values.

variable	no of blocks	mean	variance	minimum	maximum
100-kriged value	110	-0.054	0.768	-1.902	2.318
1100-kriged value	110	0.710	0.267	0.037	2.318
variable	**no of blocks**	**mean**	**variance**	**minimum**	**maximum**
100-cokriged value	110	-0.074	0.413	-1.760	2.037
1100-cokriged value	110	0.504	0.164	0.003	2.037

TABLE 6

Modified kriging and cokriging results and the actual value for the closely drilled block.

variables	kriging			cokriging			known grade
	grade	mo grade	kri var	grade	mo grade	cokri var	
y135	38.90	38.66	15.55	37.95	38.04	12.91	32.42
y145	34.18	33.90	6.86	34.18	34.28	6.85	36.94
y160	13.20	13.10	2.44	13.11	13.14	2.32	15.23
y170	4.65	4.61	0.37	4.69	4.70	0.32	3.96
y180	1.81	1.79	0.22	1.83	1.83	0.21	2.96
y190	1.77	1.76	0.07	1.77	1.77	0.07	1.97
y200	0.91	0.91	0.02	0.90	0.90	0.02	1.09
y210	0.45	0.45	0.03	0.45	0.45	0.03	0.38
yss2	4.87	4.83	0.45	4.87	4.88	0.45	5.03
sum	100.74	100.00	NA	99.75	99.99	NA	99.98

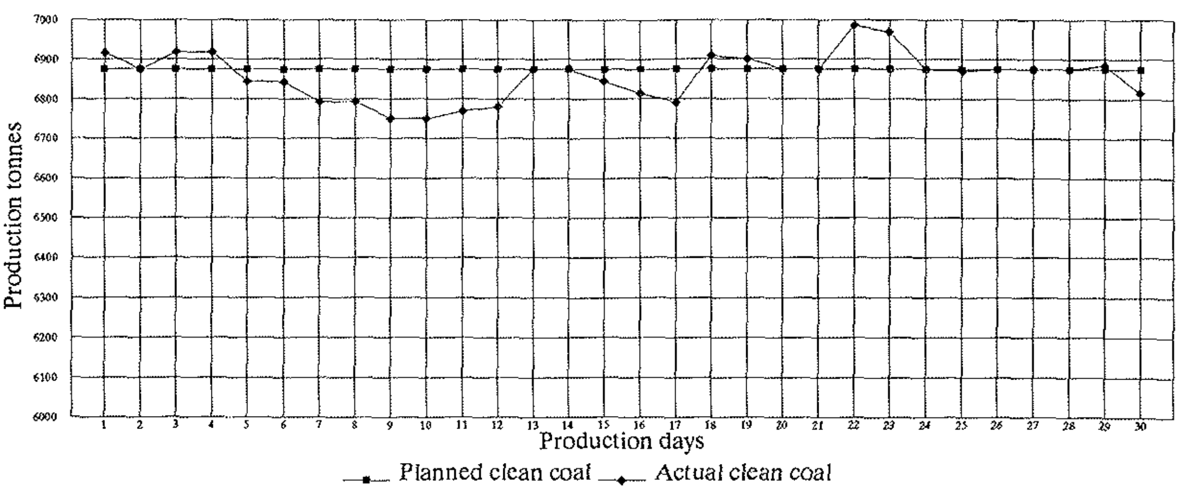


FIG 6 - Daily production fluctuation over a month.

TABLE 7
Ninety-five per cent confidence limits for the estimation.

	kriging			cokriging		
variable	kri-tru	mkri-tru	95 % confi inte	cok-tru	mcok-tru	95 % confi inte
y135	6.48	6.24	-7.73 to 7.73	5.53	5.62	-7.04 to 7.04
y145	-2.76	-3.04	-5.13 to 5.13	-2.76	-2.66	-5.13 to 5.13
y160	-2.03	-2.13	-3.06 to 3.06	-2.12	-2.09	-2.99 to 2.99
y170	0.69	0.65	-1.19 to 1.19	0.73	0.74	-1.11 to 1.11
y180	-1.15	-1.17	-0.92 to 0.92	-1.13	-1.13	-0.09 to 0.90
y190	-0.20	-0.21	-0.52 to 0.52	-0.20	-0.20	-0.52 to 0.52
y200	-0.18	-0.18	-0.28 to 0.28	-0.19	-0.19	-0.28 to 0.28
y210	0.07	0.07	-0.34 to 0.34	0.07	0.07	-0.34 to 0.34
yss2	-0.16	-0.20	-1.32 to 1.32	-0.16	-015	-132 to 1.32

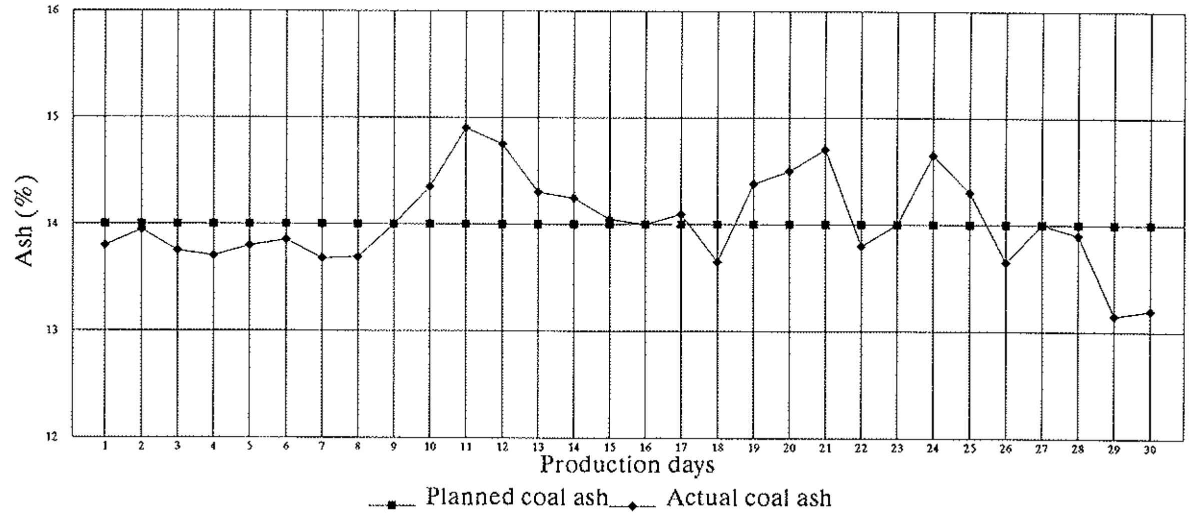


FIG 7 - Daily fluctuation of the clean coal ash per cent over a month.

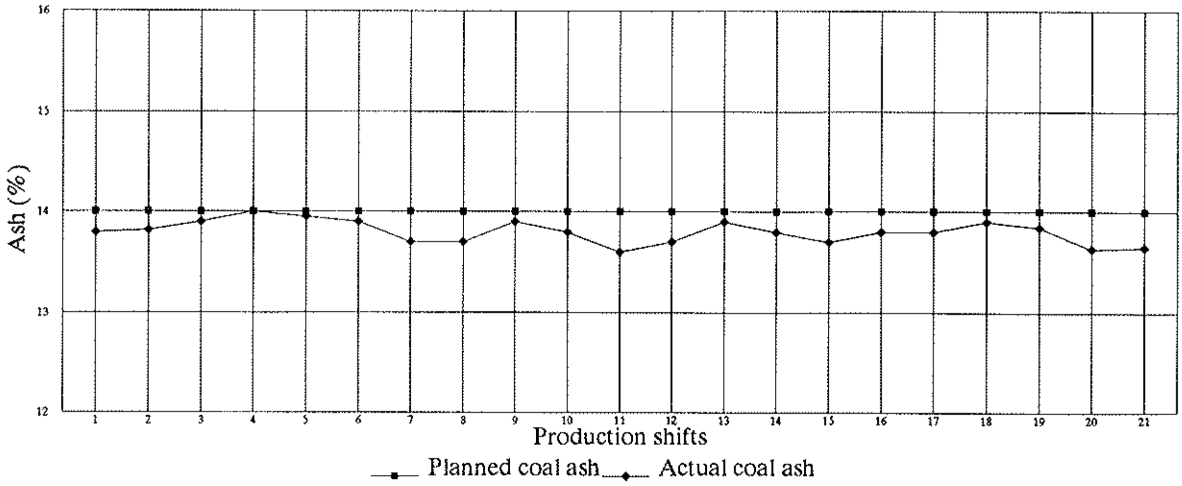


FIG 8 - The fluctuation of the clean coal ash per cent for each shift over a week.

transformed variables

3. carrying out the conditional co-simulation
4. modifying the original simulated model obtained in step (3) by quadratic programming
5. obtaining the final co-simulation model by using the correction of variances technique on the model in step 4

This procedure has proved to be very satisfactory in constructing a coal quality model. Due to the limited space, only the simulated results are presented. A small block with a dimension of 10 m x 10 m was selected as the basic unit for the simulation. Table 8 presents the means, variances and correlation coefficients for the values of the simulated small blocks and Figure 5 lists the variogram for yield at 1.35 calculated from the simulated values of the small blocks.

TABLE 8
The means and variances (a), and the correlation coefficients (b) for the simulated results.

variable	mean	variance
y13q	32.647	48.471
y14q	38.186	21.183
y16q	13.697	8.086
y17q	4.679	1.347
y18q	2.565	0.775
y19q	1.931	0.222
y20q	0.973	0.549
y21q	0.556	0.091
yssq	4.766	1.212

(a)

	y13q	y14q	y16q	y17q	y18q	y19q	y20q	y21q
y13q	1.000							
y14q	-0.773	1.000						
y16q	-0.666	0.190	1.000					
y17q	-0.323	-0.153	0.385	1.000				
y18q	-0.525	0.130	0.388	0.508	1.000			
y19q	-0.448	0.274	0.154	0.176	0.403	1.000		
y20q	-0.439	0.141	0.243	0.405	0.472	0.349	1.000	
y21q	-0.304	0.003	0.251	0.294	0.465	0.330	0.417	1.000
yssq	-0.242	0.126	-0.007	0.015	0.042	0.189	0.279	0.074

(b)

MINE SCHEDULING EXERCISES

The significance of these two models relates to improvements in mine planning and scheduling operations and better control of the preparation plant. When incorporated with a plant simulator, these two models can provide mining engineers and plant technologists with a set of powerful tools. A simple mine scheduling exercise was carried out by assuming perfect plant separation although the real power of these models is in the ability to take into account plant efficiency factors. In the exercise, the mining production rate from the seam being studied was assumed to be 2.5 million tonnes of clean coal per year. The target 14 per cent ash clean coal was assumed to be maintained in each shift according to the prediction (cokriging) model, and the production rate of the clean coal was also assumed to be maintained in each shift. Based on these constraints, production scheduling was carried out on the predicted model and the mining sequence was recorded. This mining sequence was then carried out on the co-simulation model which is supposed to represent the actual value of the deposit. Figure 6 shows the daily production fluctuation over a period of a month and Figure 7 shows the fluctuation of clean coal ash per cent for that period. Figure 8 shows a similar curve for the fluctuations for each shift for the first week of the month.

CONCLUSION

A geostatistical study on coal washability data has been successfully undertaken on closely spaced drill holes. The procedures to construct two in-situ coal quality models, the prediction model and simulation model, have been proposed. A successful modelling exercise has been carried out in the selected area. The two models provide a set of tools for improving routine planning, scheduling and plant operation. There is also promise for the models to be used in the areas of mining optimisation and coal quality control.

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