UNCERTAINTY MODELING OF ORE BODY AND GRADES USING SINGLE NORMAL EQUATION SIMULATION AND SEQUENTIAL GAUSSIAN SIMULATION: AN APPLICATION TO AN IRON ORE MINE

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE

REQUIREMENT FOR THE DEGREE OF

BACHELOR OF TECHNOLOGY

IN

MINING ENGINEERING

BY

NISHITH PANDA.

109MN0584

DEPARTMENT OF MINING ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY

ROURKELA-769008

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UNDER THE SUPERVISON OF

DR. S. CHATTERJEE

ASSISTANT PROFFESSOR

DEPARTMENT OF MINING ENGINEERING

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Rourkela

CERTIFICATE

This is to certify that the thesis entitled **"Uncertainty Modeling of Ore body and grades using Single normal Equation Simulation and Sequential Gaussian Simulation: An application to an iron ore mine"** submitted by Sri Nishith Panda (Roll No. 109MN0584) in partial fulfilment of the requirements for the award of Bachelor of Technology degree in Mining Engineering at the National institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in this thesis has not formed the basis for the award of any Degree or Diploma or similar title of any university or institution.

Date: 13th May 2013

Dr. S. Chatterjee

Assistant Professor

Department of Mining Engineering

NIT, Rourkela -769008

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Date: 13th May 2013

Nishith Panda

Roll No. - 109mn0584

Department of Mining Engineering

Rourkela – 769008

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ABSTRACT

A conventional, deterministic orebody model would lead to over estimation or under-estimation of the grade, volume and other parameters related to a deposit. This will lead to improper mine planning and thus incur huge financial risk. A proper orebody and grade modeling provide better confidence to mine owners regarding financial decision. However, only using few number of borehole data it is always difficult to come up with such type of accurate decision. Always there are certain amount of risk are associated with the estimation as well as decision. This thesis aims at providing a better risk assessment at minimizing the grade and volumetric uncertainty of the ore body. The multipoint simulation algorithms eliminate the demerits of variogram based geostatistics modeling and preserve multi-point information borrowed from training image. In this thesis, a case study of iron ore deposit from India is performed to analyses the volumetric and grade uncertainty the volumetric and grade uncertainty. Single normal equation simulation (SNESIM), a multi-point categorical simulation algorithm, was performed to measure the volumetric uncertainty of orebody. Ore volume uncertainty was performed by generating. 10 equiprobable orebody simulated models are developed. The grade uncertainty modeling was performed by applying sequential Gaussian simulation (SGSIM) with orebody model generated by SNESIM algorithm. The result shows that if the training image –based multi-point simulation is applied for ore body modeling, there would have been 7 % increase in volume as compared to traditional method. The grade-tonnage uncertainty reveals that uncertainty-based generates more high grade ores when compared with ordinary kriging method.

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Part 1

Introduction

The main aim of grade modeling is at providing quantitative definition of the variables distributed in space (Ishaak and Srivastava, 1989). The grades generally exhibit a complex details which a simple model or a standard mathematical function will fail to describe. Also as a financial point of view, the data from mineral deposit are sampled in a very sparse manner and thus represent only a fraction of the volume of the original sample. The modeler job is to make a very careful and sensible assessment in determining a ore body as well as the grades over the spatial domain as it will act as a decision for the mining company to invest a huge sum of money on a future venture (Yang, 2011)

The spatial phenomena is subjected to uncertainty which the traditional methods fail in include in their models. Thus it may lead to under-estimating or over-estimating of a reserve, which thus leads to improper mine planning and cost allocation. However, geostatistics provides a way to quantify spatial uncertainty (Chiles and Delfiner, 2009). Spatial variables are not completely random but usually exhibit an intricate relationship i.e. the nearby points usually exhibit similar or nearly equal values.

Open pit mine planning and design is traditionally based on a block model of the ore body built by using interpolation techniques, either traditional like inverse distance, nearest neighbourhood etc. or geostatistical method like simple kriging, ordinary kriging etc, from the drillhole sample data. data (Hustrulid and Kuchta, 2006) However, the uncertainties associated in the models and factors used in optimization is large, so assuming a single economic standard for a project is debatable (Menabde, Froyland, Stone, and Yeates , 2004) . One of the most important sources of uncertainty is the block model itself. The drillhole data is typically too sparse to support a unique and deterministic block model. A more realistic approach is to use conditional simulation techniques (Dimitrakopoulos, 1997) which allow the generation of a number of equally probable realizations of the block model, all of them honoring the drillhole data and the first and second order statistics of the ore body represented, respectively, by the probability distribution and variogram (Isaaks and Srivastava, 1989). Contrary to the traditional smooth orebody models, conditionally simulated orebodies provide the tools to quantify uncertainty in grade variability and the resulting effects on various aspects of open pit design and planning.

A variety of uncertainties are associated with an orebody. They include the volume, grade of the orebody, finances and cost of mining, mining requirements etc. Orebody models and their geological characteristics are known to be a major source of uncertainty and risk (Dimitrakopoulos, 1998).

This thesis focuses on the generation of an ore body model which is similar to the ore body to be extracted, with the help of geostatistical simulation . The thesis proposes application of a new method in calculating the uncertainties of the volume and grade of the orebody. The thesis aim is to generate equiprobable orebodies from a Training Image as reference using multipoint simulation and then incorporating into them grade values using

Sequential Gaussian Simualtion(SGS). Also, the thesis aims at calculating the uncertainity of grade-tonnage values of the simulations and making a comparison with the traditional methods.

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Part 2

Literature Review

Underground ore bodies are very valuable yet their shape and size are unknown. In the previous decade, several tactics or methods have been employed for solving geological modeling challenges. This is because the data available is limited and the value of the reserve is very high. With the advancement of technology new computational methods are being developed which aim at producing accurate representation of the orebody by optimally using the data. But the basis of modeling approach remains the same with topographical information and drill hole data play a crucial role in helping modelers paint a realistic picture of the orebody. Some of the methods that are being used are described below.

Irregularly distributed sample values (drill holes) are extended/distributed to field by several approaches; like triangle, polygon) b. Inverse distance methods, geostatistical methods , artificial intelligence (neural networks) (Erarslan, 2012). In the triangular method, triangles are made by joining drill holes. Average grade of the drill holes is found out by multiplying the grades of the triangular areas with the thickness of drillholes.In the polygonal method, polygons are geometrically defined by the perpendicular bisectors of the lines between all points. In the Inverse Distance method, weights are given to points and the weights are inversely related to the distance of drillhole node to the sample point. This is done by taking the weighted average of parametric distances. Generally the size of the orebody leads to a large and complex database which becomes difficult to handle my hand efforts alone. Then steps up the numerical algorithm methods and the mathematical approach. This leads to the development of various no. of software witch increasing accuracy and time saving processing.

Basic concept of geostatistics is regional variability of parameters (Matheron, 1971, 1963; Krige, 1984). In calculations with geostatistics deterministic and descriptive manner combines with probability and statistics (Mallet, 2002). The behavior of an orebody can possibly be expressed by an equation and then used in simulation if there is a mathematically explainable structure of the ore body (Sarma, 2009). When mathematical models fail to formulate variability, then probabilistic methods of statistics can be applied there as the sample values show a random behavior.

Geostatistics considers distances between sample points and assignment (or node) points along with their position and direction with respect to each other (Webster and Oliver, 2007). During estimation, the variances between sample points and assignment points along with the variances of samples within themselves are considered (David, 1977, Davis, 1973). This means, geostatistics regards not only distance relation between sample points and node point but also variation between them in relation with distance and direction (David, 1988). Geostatistical process are mainly of the following two processes- variogram modelling and kriging. The main drawback of the method is fitting a theoretical model with experimental variogram. The visual assessment and analysis of the experimental variogram depends on the person and thus debatable.

Variogram is the function of the distance and direction separating two locations that is used to measure dependence. The variogram is defined as the variance of the difference between two variables at two locations. The variogram is described by nugget, sill, and range parameter. It is a tool that measures spatial relationships. The variogram is a quantitative descriptive statistic that can be graphically represented in a manner which characterizes the spatial continuity (i.e. roughness) of a data set. (Barnes).

There are presently two types of stochastic simulation algorithms: variogram-based (Goovaerts, 1997) and object-based (Haldorsen and Chang, 1986). Variogram-based algorithms (e.g. sequential Gaussian simulation) provide greater freedom for conditioning to data of various types as they undergo the simulations one pixel at a time,. However, in variogram-based algorithms, the simulation is constrained only by two-point statistics, thus they can't replicate complex geometric shapes.

Object-based algorithms place one object or pattern at a time onto the simulation grid and build the realizations, hence they replicate the geometry of the object. However, when the data are dense as in the case for seismic surveys, they are difficult to condition to local data of different support volumes,.

Object-based algorithms build the realizations by dropping onto the simulation grid one object or pattern at a time, hence they can be faithful to the geometry of the object. However, they are difficult to condition to local data of different support volumes, particularly when these data are dense as in the case for seismic surveys.

The main drawbacks of stochastic simulation lies in the fact that they can't capture non-linewar geological complexities as they represent them in two-point statistics (Osterholt and Dimitrakopoulos, 2006). But the multiple point simulation approach uses Training Image that are able to overcome the deficiencies. A multiple point simulation(mps) concept was proposed by Journal (1992) and then implemented by Guardiano and Srivastava (1992). It incorporated the strengths of the above two algorithm. A Training Image (TI) is first made using object based algorithm which represent the patterns of the spatial variable phenomenas. The mps algorithm operates pixel-wise with the conditional probabilities for each pixel value being lifted as conditional proportions from a training image (TI). But the original implementation of the mps algorithm by Guardiano and Srivastava (1992) was not efficient as it scanned the TI at each new simulating node to take the required conditional probabilities for drawing the simulation. So SNESIM (Single Normal Equation SIMulation) was proposed by Strebelle (2000) . In the SNESIM algorithm, the TI is scanned only once and the conditional probabilities are saved in a search tree structure for future use during simulation. It is designed for modeling categories and can't be used for continuous variables.It is slow when the TI has a large no. of categorical data and this can only handle a limited no. of categories. If a data event is not repeated often enough in the TI, SNESIM algorithm doesn't consider the data and hence it is dropped which results in the poor representation of TI image pattern. This can be overcome by

using a large and pattern rich TI but this will take huge storage space as well as large computational time.

Part 3

Methodology

3.1 Orebody modeling using multi-point simulation

Indicator kriging is a method used when data are of categorical nature. Indicator Kriging values are binary i.e 0 and 1. For a random variable x , an indicator function is defined as

$$I_{(a,b)} = \begin{cases} 1, \text{ if } a<x<b \\ \\ 0, \text{ otherwise} \end{cases} \qquad \text{(Remy, 2004)}$$

Steps followed in Indicator Kriging are :
- The given values are converted to indicators, for chosen intervals (ai; bi], usually chosen to divide the range of x evenly
- The indicator variograms for each range interval is estimated.
- The kriging for each range interval is , using the usual equations and predictions obtained.

Generally variograms fail to capture geological variations from an area, thus variogram based geostatics are considered inadequate. But the multipoint geostatictics uses training image in capturing pattern.

Multiple-point geostatistics borrows multiple-point patterns from the training image, then anchors them to drillhole data. This methodology builds on the traditional two-point geostatistics (or variogram-based geostatistics), in the sense that its development strongly follows the two concepts outlined before. (Caers and Zhang,2002). Multipoint simulation takes all the patterns available in the TI, searches the most similar data event in the simulated body to be developed and then anchors the pattern into the simulation.

Both FILTERSIM and SNESIM algorithms gets conditioned to local data patterns by referring to a previously constructed structural model given under the form of a visually explicit training image and construct the image or numerical model. (Zhang et al., 2006). A sequential simulation approach is performed by traversing along every node of the current grid along a different random path defined for each of the nested multiple grids used. Simulation proceeds from the coarsest grid to the finest grid.

3.1.1 Single Normal Equation Simulation (SNESIM) simulation for orebody uncertainty analysis

The SNESIM code helps in providing a multiple-point simulation. A training image is used to represent the prior geological knowledge and contains the geological description of the orebody , is scanned to obtain the conditioning probability values for the central node belonging to a rock type category which is stored in a search tree for later use. (). Then in a sequential simulation mode, at each uninformed node, according to its specific conditioning data

event that a probability value is retrieved from the search tree, and a value is simulated from it.It is helpful in replicating complex TI but doesn't work for continuous variables

The general steps followed in SNESIM algorithm are

1. The training image is scanned and the occurrence of the data events are stored in the search tree
2. A random path is defined in which nodes are visited for simulation
3. Each node is simulated by
   a. Retrieving Data events having surrounding data and previously simulated nodes
   b. The probability distribution are calculated from the bayes equation
4. The above steps are repeated until the desired no. of iteration is completed

(Goodfellow et al. ,2012)

3.1.2 Bayes Theorem

Bayes Theorem is a direct use of conditional probabilities calculation in SNESIM algorithm. It gives a relationship that the probability of the occurrence of an event to the occurrence or non-occurrence of an associated event.

Let A be an attribute which can take I forms $\{a_i, i=1,2\ldots,i\}$. These may be either ore types, lithology of area, porosity or any other attribute types.

d_n be a data event .

n be the size of the template T.

For a data event at any location x of a template T_0, is defined by a vectors in that template. The data event isis measured by a group of categorical values $A(x+h_i)$ at location $(x+ h_i),i=1,2\ldots,n$

Now the MP conditional distribution is conditioned to a data event d_n

$$f(x: a_i| d_n)= E\{I(x,a_i)| d_n\}= P\{A(x)=a_i|d_n\} \qquad (1)$$

where $f(x: a_i| d_n)$ – conditional probability that $A(x)=a_i$ given the data event d_n

$E\{I(x,a_i)| d_n\}$ is conditional expectation of indicator function $I(x,a_i)$ given the data event d_n

$$I(x,a_i)= \begin{cases} 1 \text{ if } A(x)= a_i \\ 0 \text{ otherwise} \end{cases}$$

$$\text{Now let } S_i= \begin{cases} 1 \text{ if } A(x)= a_i \\ 0 \text{ otherwise} \end{cases}$$

This implies the value is 1 if there is occurance of d_n at that location x

Also let D=
$$D = \begin{cases} 1 \text{ if } d_n \text{ occurs} \\ 0 \text{ otherwise} \end{cases}$$

Thus (1) becomes

$$f(x: a_i | d_n) = P\{ S_i = 1 | D = 1 \} = E\{ S_i \} + \alpha [1 - E\{D\}] \qquad (2)$$

$E\{D\} = P(D=1)$ i.e d_n occurs and

$E\{ S_i \} = P\{ A(x) = a_i \}$ is the prior probability for attribute at x is a_i

A- weight associated

This leads to the following solution

$$f(x: a_i | d_n) = P\{ S_i = 1 | D = 1 \} = \{ P\{ S_i = 1, D = 1 \} / P\{ D = 1 \} \} \qquad (3)$$

 After scanning the Training image

Let the no of copies of data events in the training image be $c(d_n)$

And the no of replicates from the above set that have $A(x) = a_i$ is $c_k(d_n)$

Thus

$$f(x: a_i | d_n) = c_k(d_n) / c(d_n) \qquad (4)$$

Eq (4) forms the basis of SNESIM algorithm and the values can be obtained from a Training Image designed by an experienced geologist

3.2 Grade uncertainty modeling using sequential Gaussian simulation

SGS is a computationally faster conditional simulation technique. It requires normalization of data values and back transformation of result. Usually the simulation grid is usually large and dense, which usually leads to overlapping of neighbourhoods among the closest nodes and this. (Dimitrakopoulos et al, 2001)

Sequential Gaussian SIMulation (SGSIM; Deutsch and Journel (1998)), was introduced as a solution to the smoothing problem of kriging. Sequential simulation algorithms are 'globally' correct in that they reproduce a global structured statistics such as a variogram model, whereas kriging is 'locally' accurate in that it provides at each location a best estimate in a minimum

error variance sense, regardless of estimates made at other locations. The main demerit of the SGSIM is the maximum entropy property of any multivariate Gaussian model which states that a Gaussian model is the least structured among the models with same covariance.

General steps involved in SGSIM are as follows

1. Data is transformed into "normal space"
2. A grid network and a coordinate system is established
3. Data assignment to the nearest grid node is decide
4. A random path is defined that passes through all the grid nodes and
   a. Searches for nearby data and previously simulated grid nodes
   b. The conditional distribution is constructed by kriging
   c. From the conditional diustribution, simulated value is drawn
5. Back transformation and then results are checked

3.3 Proposed approach

Uncertainity Modelling of an ore body using SNESIM and SGSIM

The 1st step is the generation of a training image (TI) and data from drill hole composite using SURPAC software. The ore values in the borehole date are binarized by giving value depending on the availability of ore (1) or waste (0) at a particular location. The vertical sectioning was performed to see the ore an waste in a graphical window. The ore zone in a specific section was digitized by manual digitization method is surpac software. After, generating number of digitized sections, they are stitched together to form a solid orebody model. The solid model was then placed inside a block model with a block size of 20 m x 20 m x 10 m. The block model was then used as training image for SNESIM algorithm. The SNESIM Algorithm was implemented to produce realization uncertainty analysis of oreboy model. After the SNESIM realizations are complete, the simulated models with the highest, lowest and median volume are identified. SGS simulation was implemented to analysis the grade uncertainty within the oreboddy.

3.4 Grade Tonnage Calculation

The aim of the grade-tonnage calculation is to determine how much tonnes of metal is present in the ore body deposit for different grades of ore. It is calculated by the formula

Grade-tonnage = D_x x D_y x D_z x T x n

Where D_x , D_y , D_z = dimension of block in x,y,z directions respectively

T= tonnes of ore per m^3 of block (also called the tonnage factor)

N= no of blocks

Grade-tonnage for the maximum, minimum and median simulated blocks are calculated

Part 4

Case Study

The study was carried out in a iron ore mine. The mine has a highly undulating ground level and it is a hilly deposit. The mine is 1296m above the Mean Sea Level (MSL) and the lowest point of mineralization is at 950m below reduced level . The mine is surrounded by green vegetated area and uis well drained by nalas on both sides. The iron ore formed was formed during the Precambrian age, which was found out during the geological investigation of the area. The deposit is highly disturbed with occurrence of folds, faults. The iron ore bodies are found on the top of the range and bottom of the underlying shale. The deposit is found in the southern ridge of the range. Seven types of lithology is found in the area. They are Steel Grey Hematite(SGH), Blue Hematite (BH), Laminated Hematite(LH), Laterite(L), Blue Dust (BD), Shale (S) and Banded Hematite Quartzite(BHQ). There were 77 boreholes from which datas were collected for the study. The borehole distance was between 200-250 m and were located in a grid pattern. The average depth of the mine is about 160m. The block size is 20 m x 20 m x 10 m. Figure shows the boreholes of the case study (Fig 4.1)
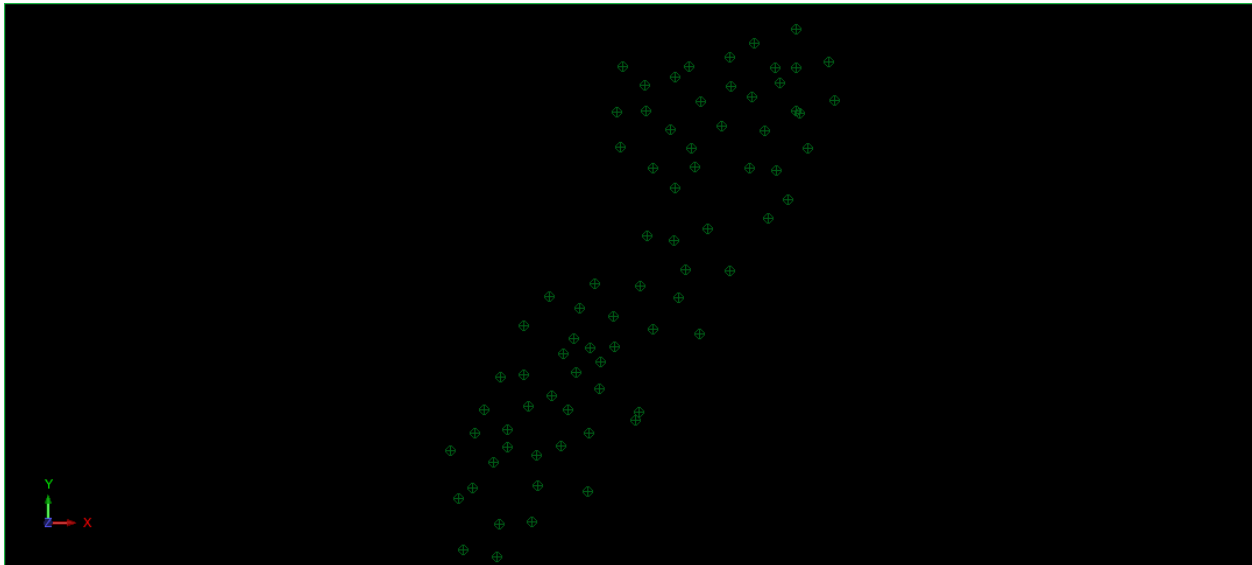

Fig 4.1 Top view of Drillhole

Part 5

Results

5.1 Geological modeling of the deposit

Data from 77 boreholes were obtained from the mine. The data in the borehole contains information about the coordinates of the boreholes, the lithology present, and the grade of the ore and the depth of the borehole. The borehole data are imported into SURPAC. After uploading the data into a SURPAC database, 50m sections along north-south direction with zone of influence of 25 m both the sides are created and then strings are created in such a manner so as to accommodate the ore portions of the drill holes and reject the waste portions. For the borehole data, the data values of coordinates where the ore value is above 60% is taken as 1 and rest are taken as 0. This is done because as a general principle in the iron ore mine under study, the cut-off grade was taken to be 60 %

The string files are extended to either side of the drill holes to indicate the influence of the ore just beyond the drillhole regions. A total number of string files were generated. After the string files are completed, they are combined a single string file. After performing the errors checking of combined string file, a solid model is created. The solid model was then placed inside a block model of dimension 20 m x 20 m x 10 m. The block model was then used as training image for orebody simulation. The orebody model inside the block model is presented in (Fig 5.1)

5.2 Orebody modeling using multipoint simulation
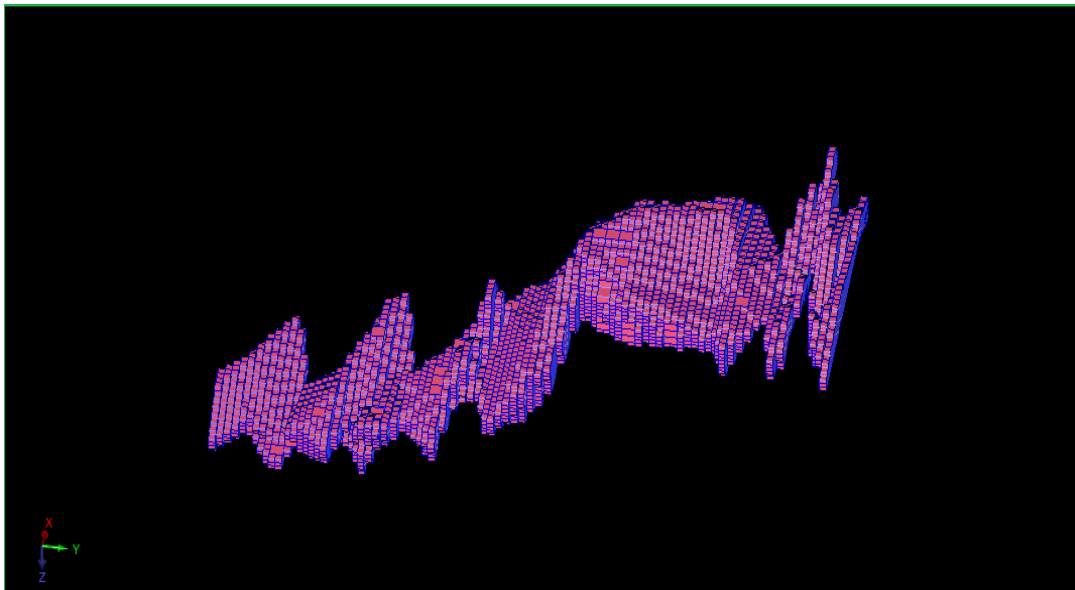

Fig 5.1 Training Image

The training image of figure and binarized borehole data of figure are used for orebody modeling using SNESIM algorithm. SNESIM is done for calculating the volumetric uncertainty in the ore

body. The template size to 15 x 15 x 9 is used. Table presents different parameters used for SNESIM algorithm.

Table-5.1 :- SNESIM Parameters

Parameters	Values or Names
Seeds	211177
No of realizations	10
# of categories	2
Target Marginal Distribution	0.96 0.04
# of nodes in search templates	60
Ranges	Max-700 Mid- 500 Min-150
Angles	Azimuth-0 Dip- 0 Rake- 0

   10 simulations are stored in a simulation grid which are further used for SGSIM. The ore volume generated by SNESIM algorithm are different from ore realization to another realization while preserving the nearly approximate shape. The blocks with the Maximum, Minimum and Median no of ore blocks over all simulated realizations are named as max, min and mid respectively. The number of maximum, median, and minimum ore block are 45007, 41319, and 38180 respectively. Below are the (fig 5.2 (a), (b) and (c)) of the generated simulations using SNESIM algorithm. The figures shows the size of the simulations being nearly equivalent to the training image.
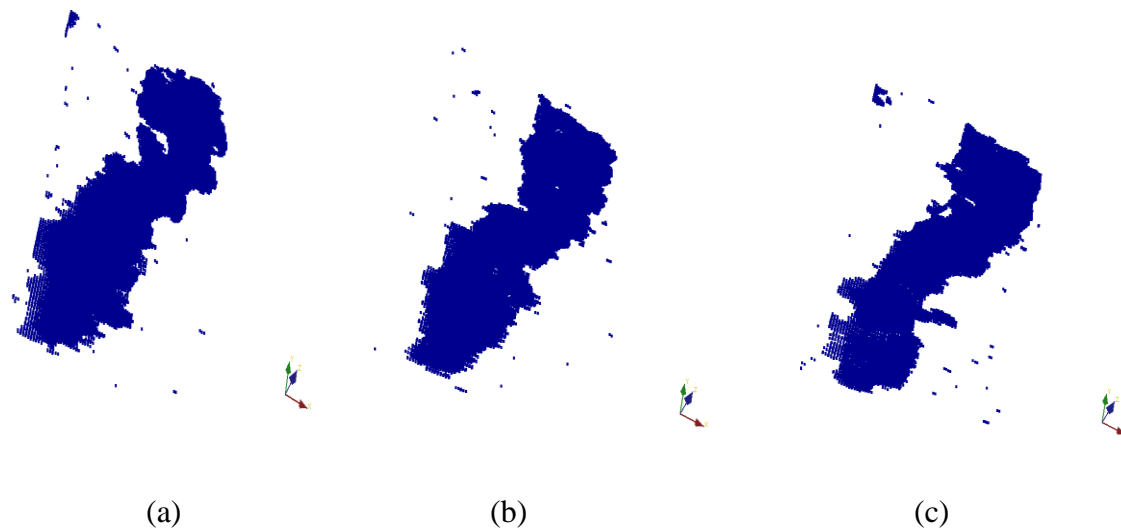

(a)   (b)   (c)

Fig 5.2 SNESIM Realization of (a) MAXIMUM Volume (b)Median Volume (c)Minimum Volume

5.2.1 Validation of SNESIM results

To evaluate the uncertainty of volume and grade-tonnage of the orebody; 10 SNESIM realization are generated. The simulation is done on a replica of the grid on which the TI is described. However, to check the performance of the proposed method, one-point (histogram/proportion) and two-points (variogram) statistics were performed, Variograms of the SNESIM realizations are computed along with the variograms for the TI and the composite (or hard) data. It is seen that the variograms of the realization (Fig 5.3 (a), (b) and (c)) is closely related to TI. This is because SNESIM uses patterns from the TI and uses them in the simulation. The difference in the variogram value can be minimized by post processing operations or by increasing the number of nodes which increases information to a simulated node. But this will increase the cost as well as processing time and thus is avoided. (Goodfellow et al., 2012)
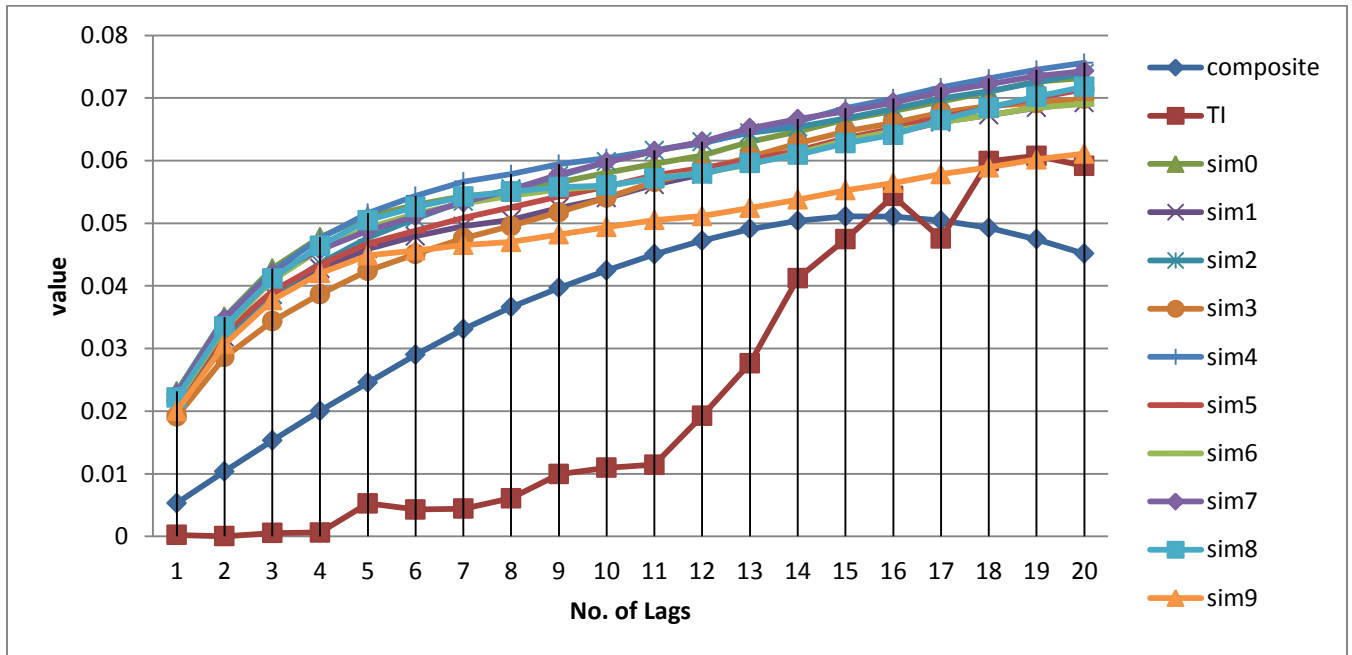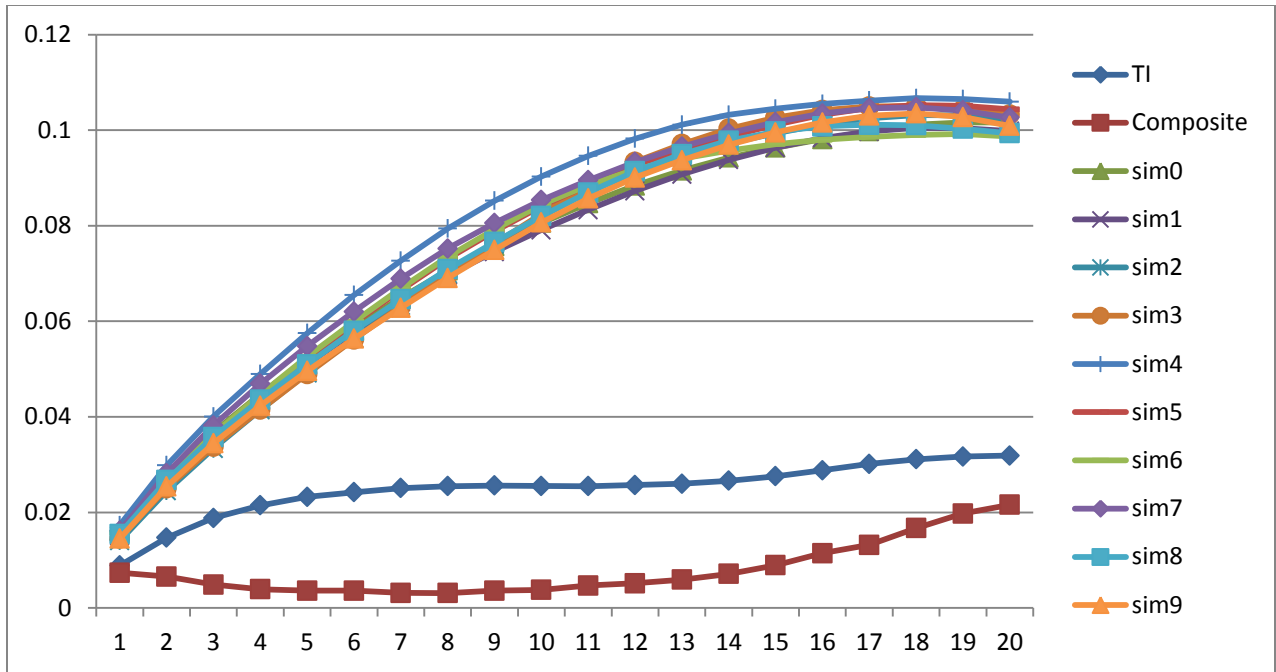

Fig 5.3 (a) Variogram in Y direction
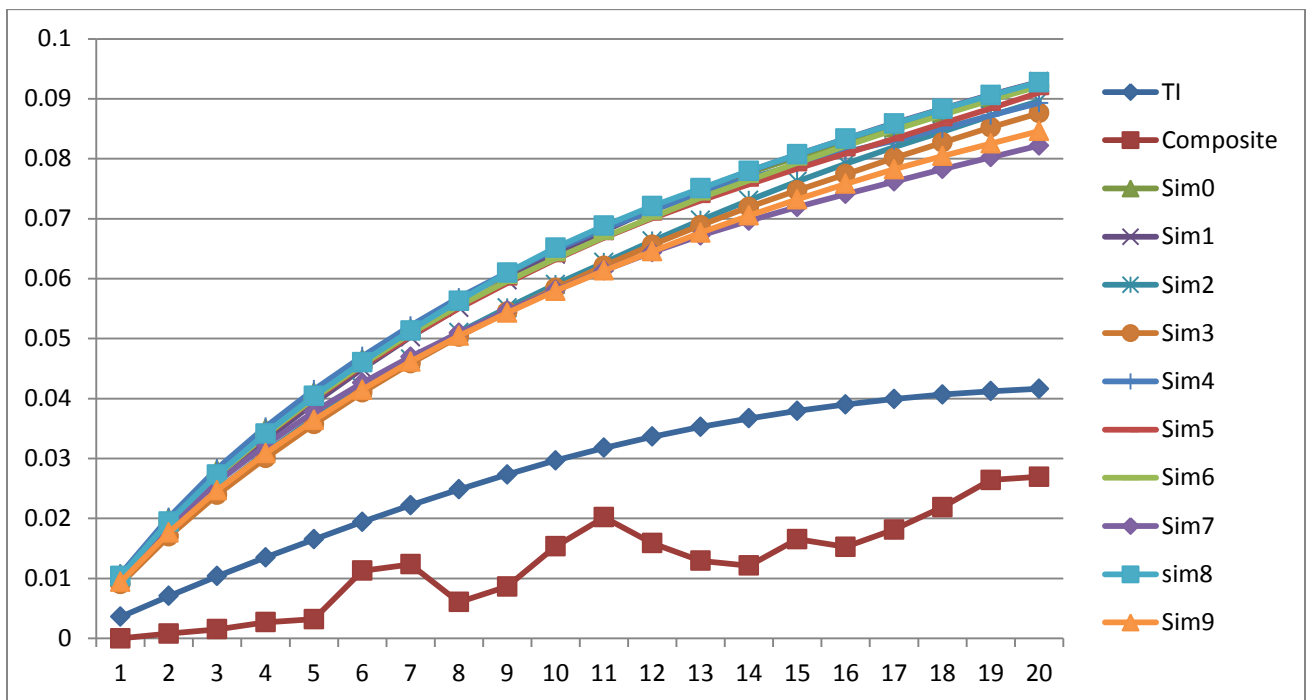
Fig 5.3 (b) Variogram in Z direction

Fig 5.3 (c) Variogram in X direction

The Ore-Waste proportion in the TI, Composite data and the 10 SNESIM simulations was carried out and presented in (Fig 5.4). It showed that the simulations represented a near value to the Composite or the hard data.
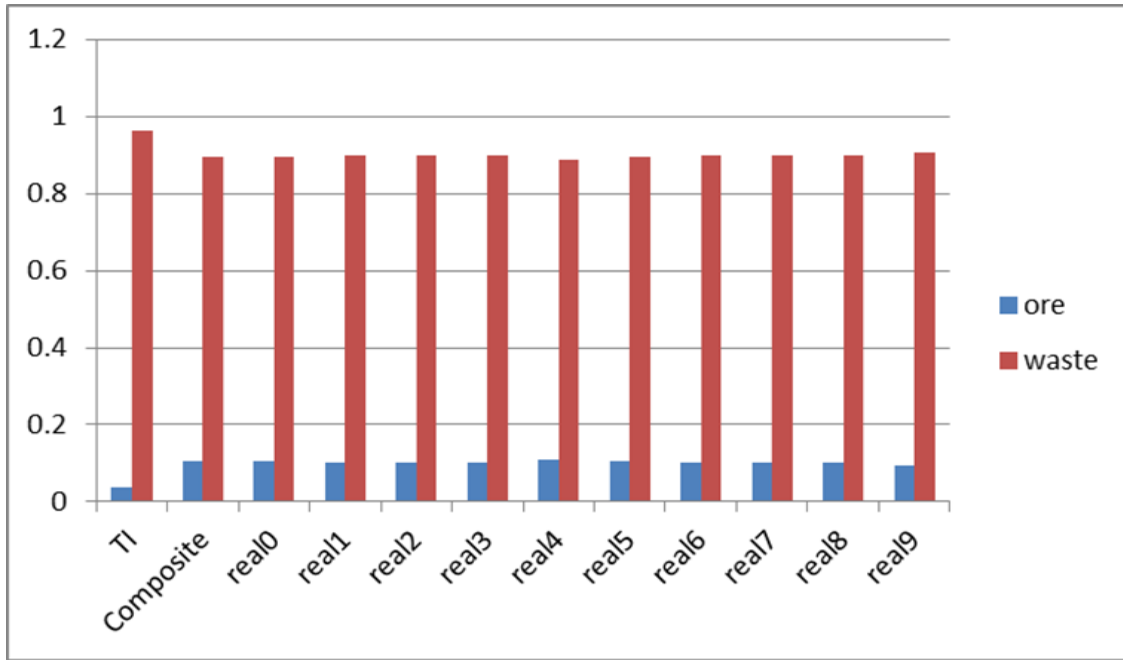

Fig 5.4 Ore waste proportions of Training Image, Composite data and SNESIM Realizations

5.3 Grade uncertainty modeling using SGS

To perform the grade uncertainty modeling, the simulation of grades were performed inside the orebody model simulated SNESIM. The 5 m composite data were used for grade uncertainty modeling. The composited borehole data were first transformed to normal score domain . The variogram of the normalized grade data were performed and fitted with spherical variogram model. (Fig 5.5 (a), (b) and (c))
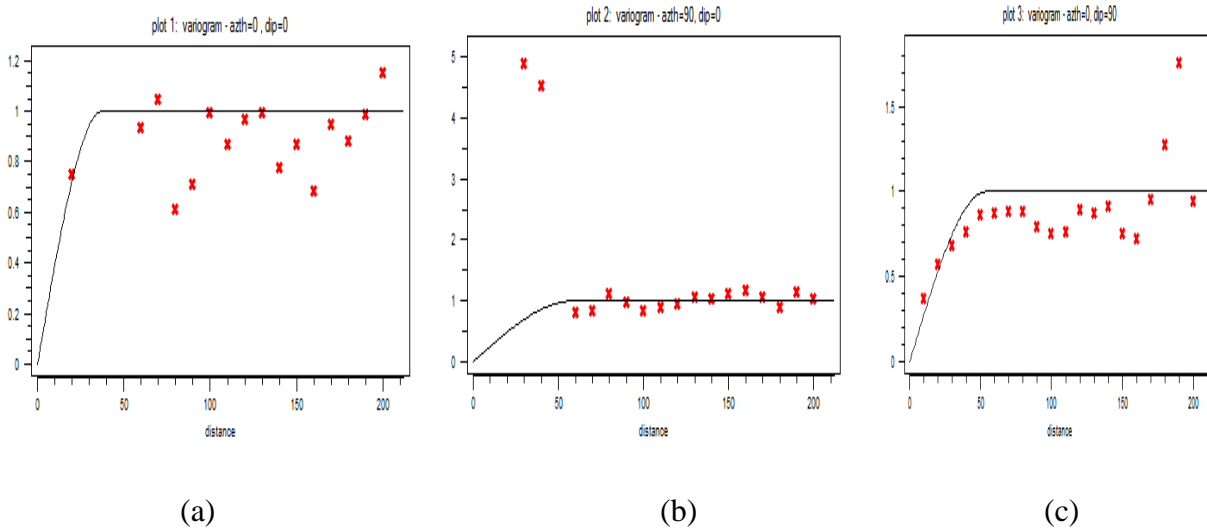
Fig 5.5 Variogram of the normalized ore used for SGSIM Simulation in (a) X direction (b) Y direction and (c) Z direction

The sill value is 1 and the Max, Med and Min values of range are 120,80,30 respectively. The angular values are 85,45and 46. Figure shows the experimental and theoretical variograms in 3 different directions. Figure demonstrates that theoretical variogram is nicely match with experimental variograms.

5.3.1 SGSIM

SGSIM is used for calculating the grade tonnage uncertainities in the realizations obtained by the SNESIM algorithm. By using SGSIM algorithm, grade values are incorporated into the simulation models

Table-5.2 :- SGSIM Parameters

Parameters	Values or Names
Seeds	14071788
No of realizations	10
Kriging Type	Ordinary Kriging (OK)
Max Conditioning Data	12
Ranges	Max- 120 Mid- 80 Min- 30
Angles	Azimuth-85 Dip- 45 Rake- 46
Nugget Effect	0

No of Structure	1
Contribution	1
Type of Histogram	Spherical

The grade maps are now shown on the models that were generated by SNESIM. After SGSIM, the models look as shown in (Fig 5.6)

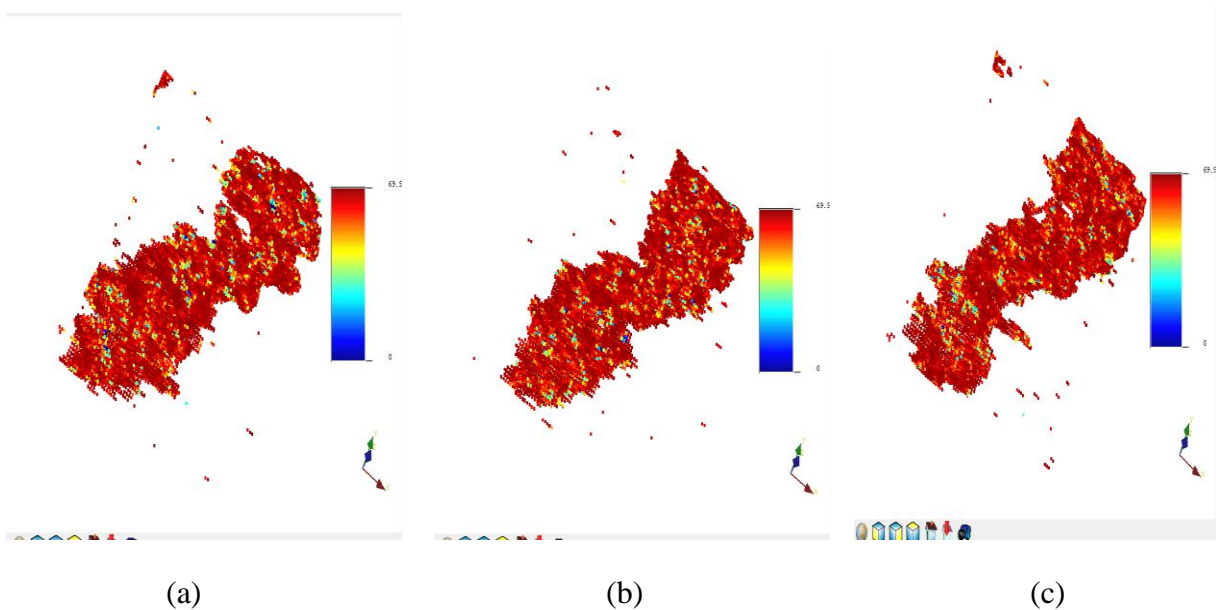(a)   (b)   (c)

Fig 5.6 SGSIM Realization of (a) MAXIMUM Volume (b)Median Volume (c)Minimum Volume

For validating the SGSIM results. the variograms of the grade within the Maximum, Median and the Minimum simulated orebody models are computed against the composite data., which indicate erratic behavior of hard data in the X and Y direction while in the Z direction, the behavior is smooth. The simulations have a smooth behavior in all the 3 directions.(Fig 5.7 (a), (b) and (c)).
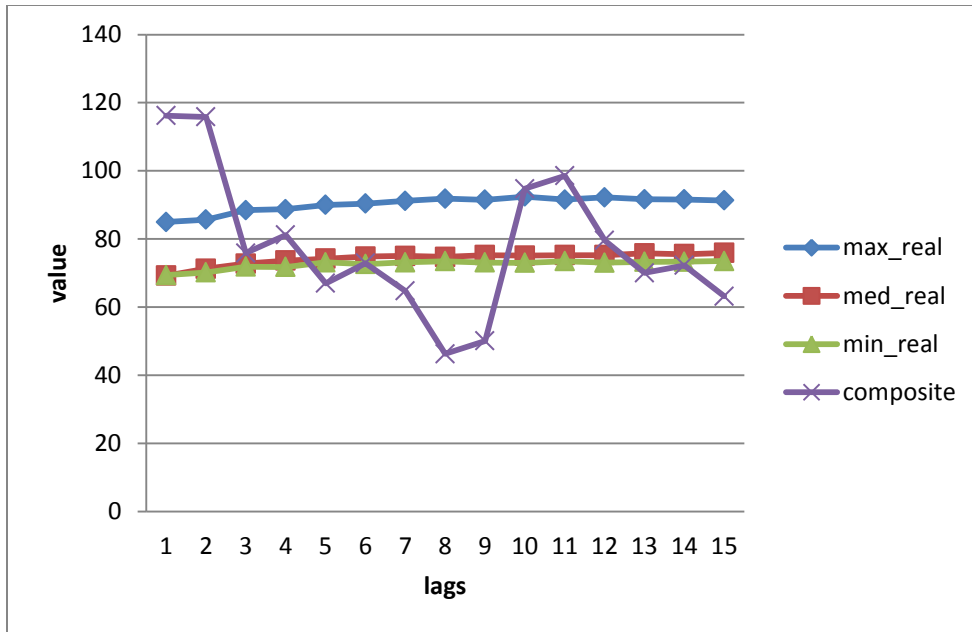
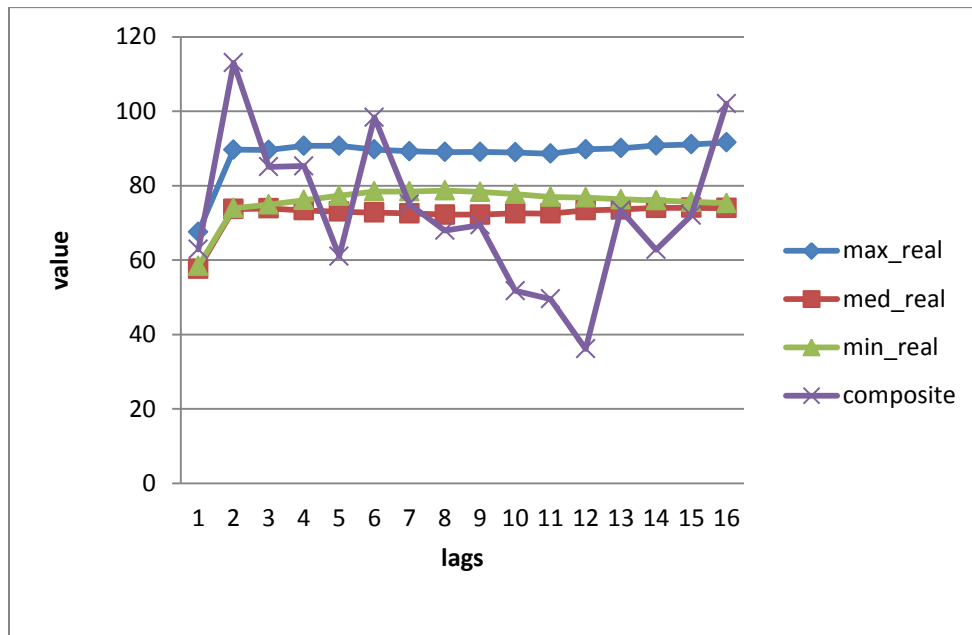Fig 5.7(a) Ore Variogram in Y direction

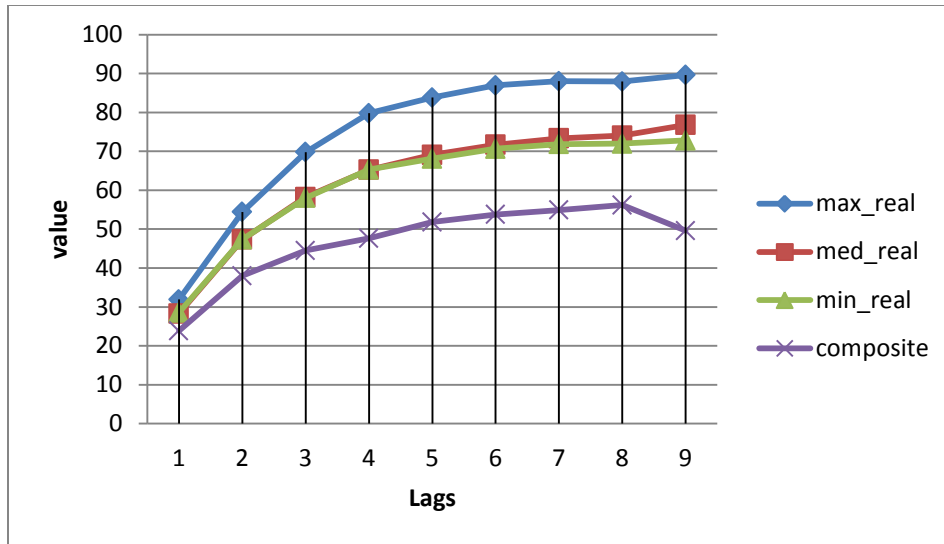Fig 5.7(b) Ore Variogram in X direction

Fig 5.7(c) Ore Variogram in Z direction

5.4 Grade-tonnage curve

The Grade Tonnage Curve of the simulated model above the cutoff grade (> 60%) is also in close proximity with the Ordinary Krigging result of the the respective model. The graphs highlight the demerit of a traditional method as it can be seen that above the cut-off grade, the ordinary kriging shows lower no. of blocks than the simulations , thus resulting in erroneous assessment of high grade ores. The no of blocks that are higher in the Max,Min and Med simulations are 532, 790 and 1542 respectively (Fig 5.8 (a), (b) and (c)).
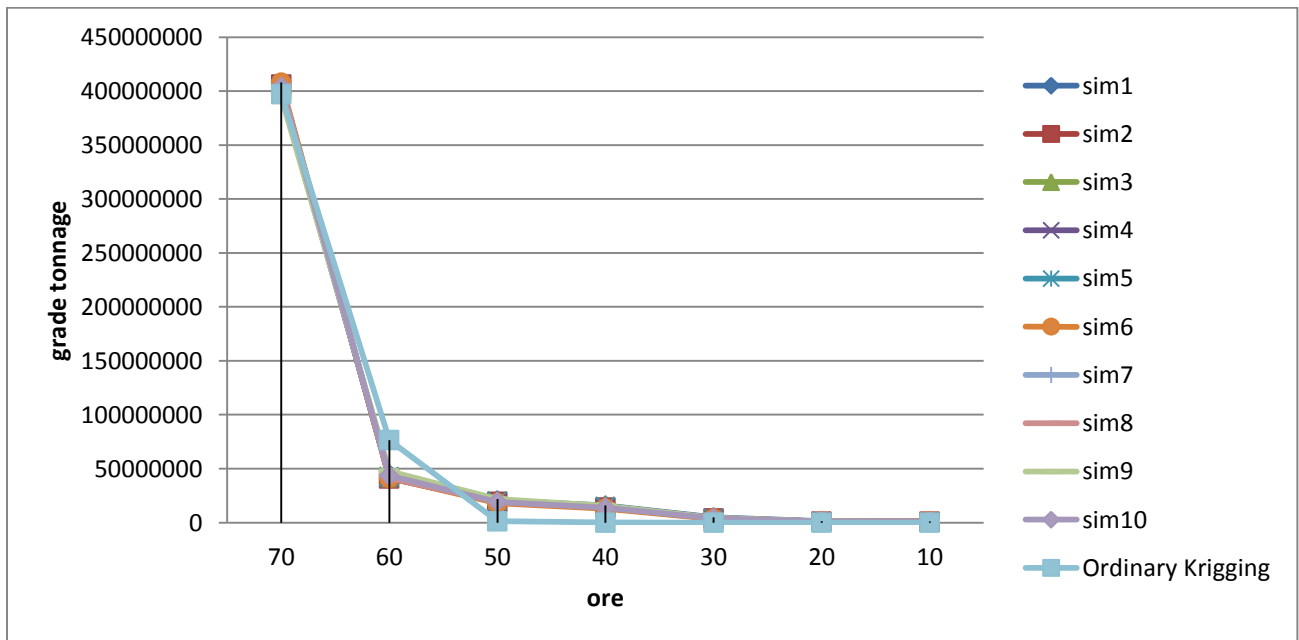

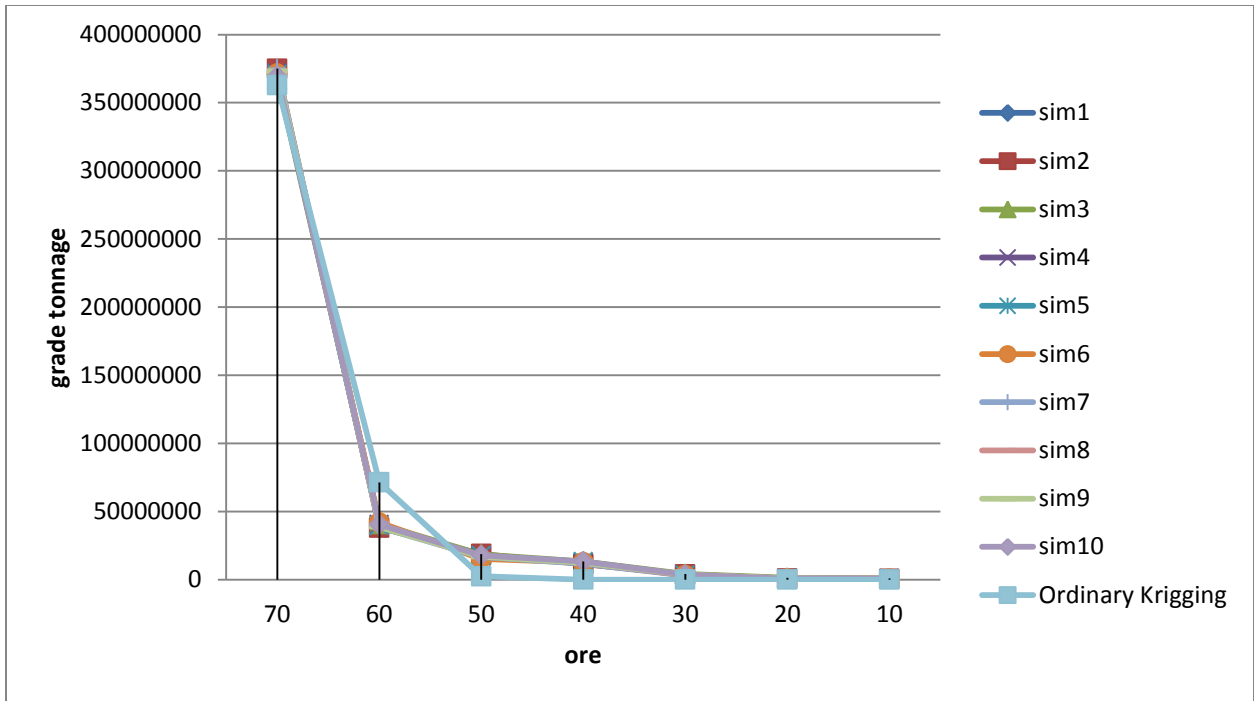Fig 5.8 (a) Grade Tonnage curve of Maximum Simulation Model

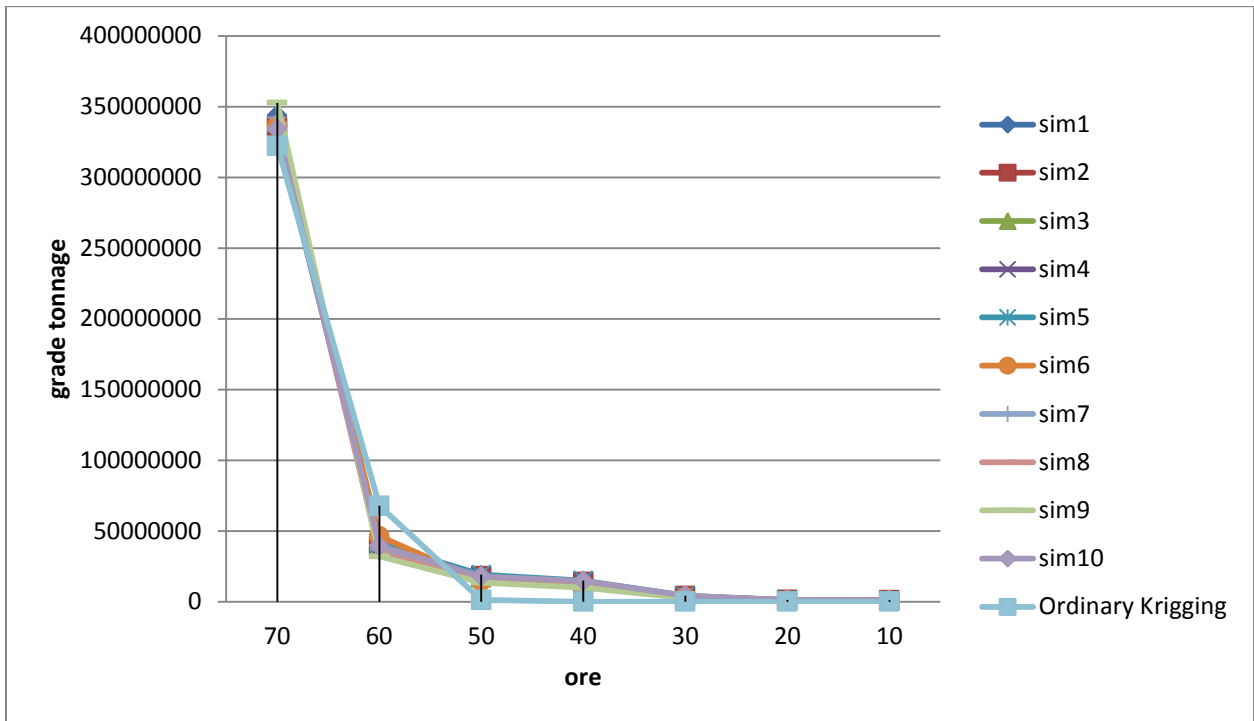Fig 5.8 (b)Grade Tonnage Curve of the Median Simulation Model

Fig 5.8 (c) Grade Tonnage curve of the Minimum Simulation mode

Part 5

Conclusion

This thesis makes an attempt at assessing the volumetric and grade uncertainity related to a iron ore mine. A deterministic model was developed and used as Training Image. Using the borehole data, composites of 10 m length were created. For better quantification of the volumetric uncertainty and to show the spatial relationship, SNESIM algorithm was implemented to generate a set of 10 equiprobable ore bodies. Then to understand the grade uncertainity, the simulated models were provided grade values from the composite data models by using SGSIM algorithm. The result showed that the simulated ore bodies and the composite data had nearly equal spatial relationship and the Training Image differed a bit from the simulated ore body . The volumetric uncertainty between the TI and the simulated models showed a difference of about 7 %. . The uncertainties of the grade-tonnage of the simulated ore was compared with a traditional method and a difference was noted above the 60% cutoff grade. This will help in the proper mine planning and also there will be lesser financial cost.

Part 6

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