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Proceeding Paper

Application of Machine Learning to Resource Modelling of a Marble Quarry with DomainMCF †

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Abstract: Machine learning is constantly gaining ground in the mining industry. Machine learning-based systems take advantage of the computing power of personal, embedded and cloud systems of today to rapidly build models of real processes, something that would have been impossible or extremely time-consuming a couple of decades ago. The widespread access to the internet and the availability of cheap and powerful cloud computing systems led to the development and acceptance of tools to automate resource modelling processes or optimise mine scheduling, using machine learning methodologies. The domain modelling system discussed in this paper, called DomainMCF, has been developed by Maptek, using artificial neural network technology. In the application presented in this paper, DomainMCF is used to model the spatial distribution of marble quality categorical parameters, and the results are combined to produce a final marble quality classification using drillhole and quarry face samples from an operational marble quarry in NE Greece. DomainMCF was made available for this study as a cloud processing service through an early access program for individuals or companies interested in testing its capabilities and suitability in various modelling scenarios and geological settings. The resulting marble product classifications are compared with those produced by the already established classification system that is based on a more conventional estimation method. The produced results show that DomainMCF can be effectively applied to the modelling of marble quality spatial distribution and similar domaining problems.

Keywords: quarrying; geological modelling; resource estimation; machine learning; neural networks; marble quality

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1. Introduction

Resource modelling and estimation of natural stone deposits such as the marble deposits in Greece has been the subject of research in the past [1–3]. The company that provided data for this study is Iktinos Hellas, one of the major marble quarrying companies active in Northeastern Greece. Iktinos is a vertically integrated company with four privately owned marble quarries, three cutting and processing factories, a local sales network and an ever-growing sales network abroad. The Laboratory of Mining Informatics and GIS Applications of the Department of Mineral Resources Engineering at the University of Western Macedonia is supporting Iktinos Hellas in developing and implementing solutions for marble resources estimation and quarry design and modelling. The marble deposit, used in the present study, is in the Volakas area NW of the city of Drama. Volakas is hosting several significant marble quarries.

Depending on the actual marble products produced and market needs, some general categories are commonly used, such as A, AB, B, BB, C and waste. These general categories or classifications are based on marble mass visual and structural parameters which can also be different from quarry to quarry. These parameters include marble characteristics such as background colour, texture, presence of veins, discolouration and discontinuities of different scale. Parametrisation of marble samples and classification to one of the categories is performed by experienced personnel, and is based on samples much smaller in area than the blocks of marble which are potentially exploited. The use of standard estimation and modelling software tools in estimating marble quarry reserves poses a few challenges, as the available information is mostly qualitative [3].

2. Marble Samples Characterisation and Conventional Resource Modelling Method

In the marble deposit of the present study, the following parameters were identified and used to characterise the marble features that are significant to its quality classification:

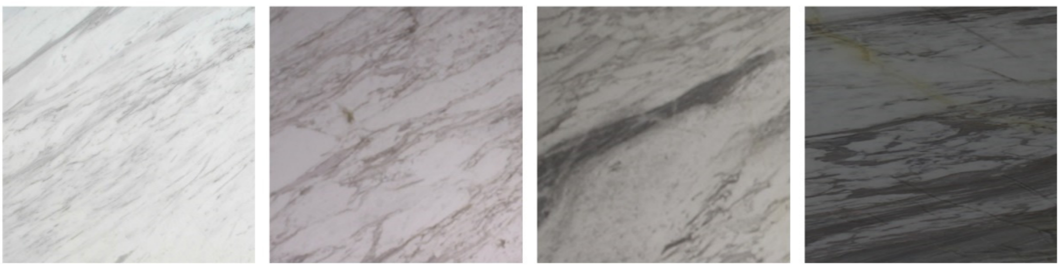
- Lithology (dolomitic or calcite);
- Type (flower-like or diagonal-vein features);
- Background (presence of visible defects);
- Tectonic features (discontinuities of varying orientation).

Two main marble types are identified in the deposit based on the shape of the veins and are also modelled and used to control the marble classification (Figure 1). There are four more marble types, but these are not considered as commercially exploitable marble.

(a) (b)

Figure 1. Main marble vein types: type L (**a**), and type D (**b**).

The next parameter is background. It represents colour and vein density and thickness. As shown in Figure 2, Volakas marble is categorised into four different background types: (1) white background with homogenously distributed thin veins or flowers with no presence of calcite crystals and steins (yellow or red lines), (2) slightly darker background with veins or flowers of varying thickness with some calcite crystals (glass), (3) dark background with veins or flowers of varying thickness and many calcite crystals (glass) and steins (yellow or red lines) and (4) very dark background with veins or flowers of varying thickness with dense calcite crystals (glass) and steins (yellow or red lines).



(1) (2) (3) (4)

Figure 2. Examples of different marble background types.

Tectonic features are also represented using four parameters corresponding to four groups of discontinuities of different dip direction/dip (tecto1—40/40, tecto2—210/70, tecto3—320/55, tecto4—20/80). The presence and intensity of each group in the marble mass lead to a different category for each of the parameters.

All the available information for marble resource estimation is categorical, leading to the use of indicator methods such as indicator kriging or some other interpolator of indicator values. Iktinos Hellas has been using Maptek Vulcan Quarry Modeller since 2014 and has implemented a methodology based on inverse distance interpolation of indicator values for the various marble parameters discussed [3]. In this process, each of the marble parameter values is associated with an indicator field which can be either 0 or 1, depending on whether the sample is classified to have the specific parameter value, e.g., if a sample is considered to be TYPE L, then the field L_PR = 1 and field D_PR = 0. A database field calculation script is employed to fill these extra binary fields with values based on the original parameter fields.

A regular block model is used consisting of blocks sized according to volumes (slabs) separately extracted at the quarry. Samples are selected around each block using search ellipsoids which are oriented according to the geological features of the deposit. Each block receives a final marble classification by consolidating the interpolated indicator field values using a block model script. This method is constantly fine-tuned to produce results closer to the quantities produced by each quarry. Still, it is a time-consuming process, suffering from the usual issues resulting from highly irregular sampling patterns, and the subjectivity of the original sample characterisation.

3. Domain Modelling Methodology

DomainMCF, a machine learning-based system developed by Maptek, was used to model the spatial distribution of the marble quality characterisation parameters described in the previous section, and the resulting values were combined to produce a final marble quality classification. DomainMCF was made available as a cloud processing service through an early access program for individuals or companies interested in testing its capabilities and suitability in various modelling scenarios and geological settings. DomainMCF is based on artificial neural network (ANN) technology to model the spatial distribution of discrete domain values from a set of samples.

ANNs, such as those developed by DomainMCF, typically have an architecture, as shown in Figure 3 [4]. The ANN consists of multiple layers of processing elements (PEs) also known as *neurons*. There are three types of layers and corresponding PEs—input, hidden and output. PEs from one layer are connected to PEs in the next layer using weighted links known as *synapses*. PEs transfer the input signal to their outputs using an activation function that differs between the three types of layers. The number of input PEs is controlled by the way samples are presented to the ANN, i.e., the input space configuration. Researchers in the field of ANN application to grade/resource estimation have used multiple configurations of the input space [5–12]. The number of hidden layers and PEs per hidden layer can be fixed or controlled by an optimisation process that will find the best configuration according to some performance criteria. Typically, the number of network inputs and outputs and the complexity of the required mapping between them will lead to a different number of hidden layers/PEs. The number of PEs in the output layer is controlled by the number of variables to be modelled.

Learning from examples is the main operation of any ANN. In general terms, learning means the ability of an ANN to improve its performance, defined with some measure, through an iterative process of adjusting its free parameters (weights, number of PEs, etc.). The adjustment of an ANN's free parameters is stimulated by a set of examples presented to the network during the application of a set of well-defined rules for improving its performance called a learning algorithm.

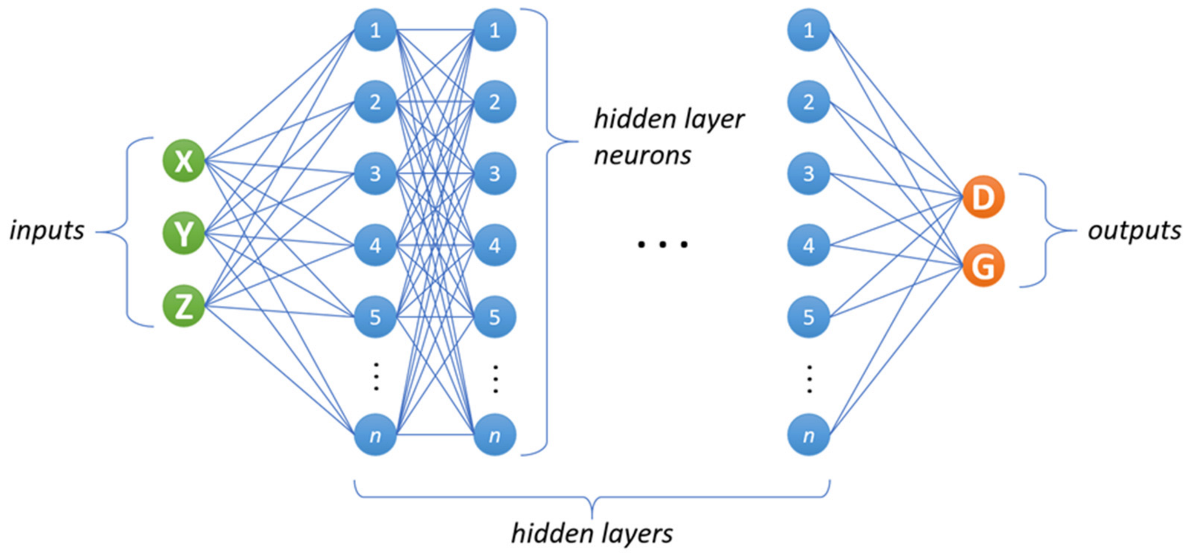


Figure 3. Simplified architecture of the artificial neural network used for domain modelling [5].

In the case of DomainMCF, sample X, Y, Z coordinates are used as inputs and the sample domain (D) and, optionally, sample grade (G) are used as the required outputs. When both sample domain and grade are used as outputs, the synaptic weights between PEs of successive hidden layers will be affected by both distributions during training, thus leading to some dependency between the learned mappings for each variable.

ANN development is data driven and thus largely dependent on the quantity of data. Generally, in the case of domain modelling for grade/resource estimation purposes, more samples will be required to produce a representative model in a more geologically complex scenario. A more complex ANN architecture with more PEs and hidden layers, allows a more complicated model to be generated (through development) but also requires more data. After development, the ANN can be used to get output values for any set of X, Y, Z coordinates presented at its input layer (e.g., block centroid coordinates), even outside of the sample coordinates range. However, outputs produced in areas outside of the range of examples introduced to the ANN during development should be treated with caution and examined carefully as to their validity, as in any case of extrapolation by more conventional methods.

4. Application and Results

For the requirements of our DomainMCF study, sample data were composited in seven separate CSV files, one for each of the marble quality parameters (lithology, type, background, tecto1, tecto2, tecto3, tecto4). Each file was used in a separate run of DomainMCF to develop the underlying network. A block model definition file was also provided to control the application area and locations for DomainMCF. Block centroids are used by DomainMCF as network inputs to control the locations of application, once training with the sample data is complete. The application area was also limited by an upper and lower triangulation surface—the topography and a lower base surface. During setting up of the input data for DomainMCF, the CSV is displayed, and the user can nominate the three columns that correspond to the sample XYZ coordinates (inputs), plus the domain and grade columns (outputs). DomainMCF will then train its network to develop the mapping between them.

The predicted values from the produced block models of all seven runs were exported to ASCII files and imported to a single block model that also contained classifications from the conventional system, to consolidate the results and allow for easier comparison between the two methods. Figure 4 shows the final marble products based on the predicted marble classification parameters for the case of the conventional system (a), and DomainMCF (b).

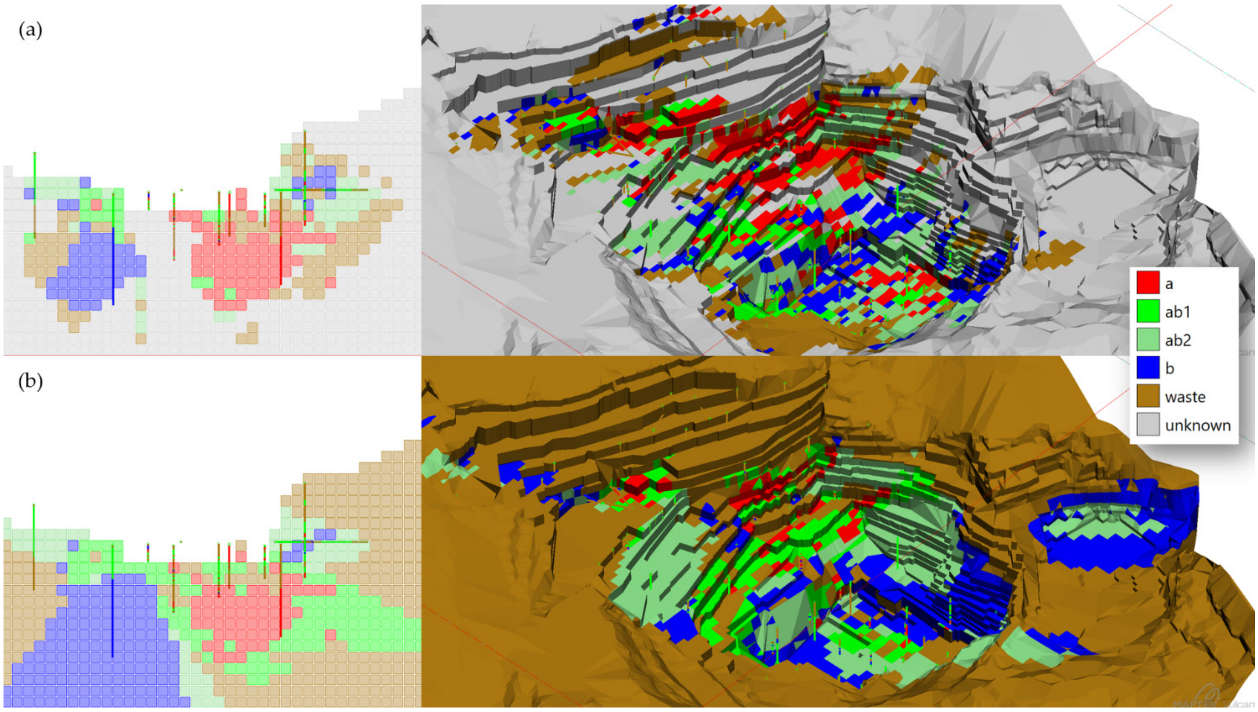


Figure 4. Cross section (left) and 3D view (right) of conventional method (**a**), and DomainMCF predictions (**b**). ID2 estimates were limited by a search ellipsoid while DomainMCF was free to estimate the entire block model.

As with any other estimation or classification system, it is necessary to have tools to measure the local confidence of the results. DomainMCF produces a confidence level value for its predictions. This is calculated during network development and gives some measure of the system's certainty on the produced domain value at each location. Domain confidence can be used to identify areas where it is more difficult to be certain about the predicted domain value, for example, areas where more sampling is required, or existing samples have higher local variability. Figure 5 shows horizontal block model sections coloured by the domain confidence value for each of the predicted marble parameters.

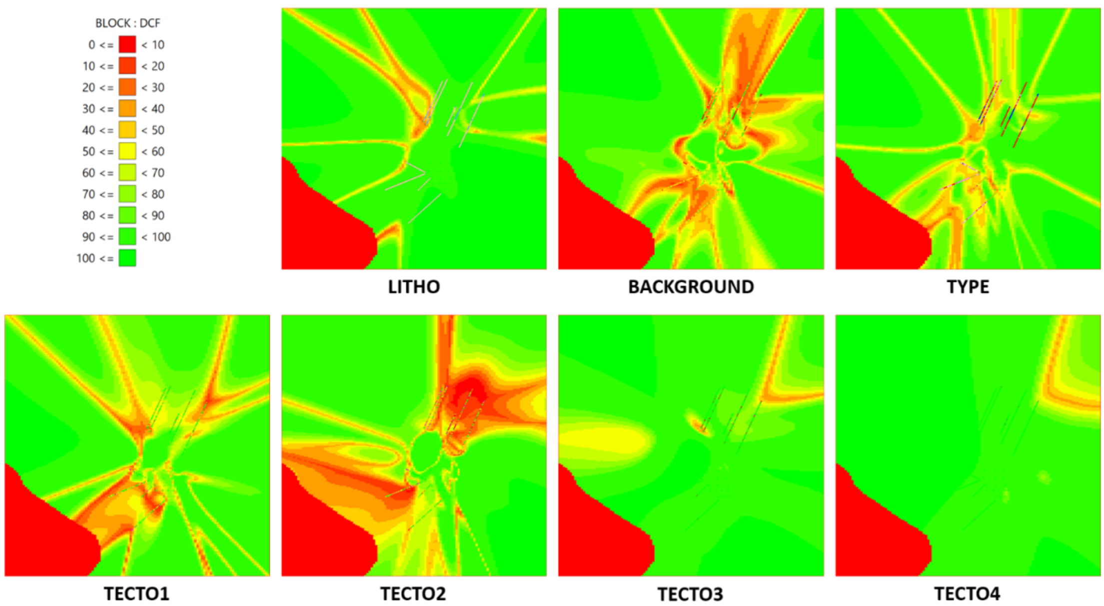


Figure 5. DomainMCF prediction confidence levels.

5. Conclusions

The application of DomainMCF proved to be an extremely quick way to produce marble classifications based on drillhole and other data, with more uniform and more reasonably distributed marble classifications compared with the conventional modelling method. It requires no structural analysis of the modelled categorical parameters. Sampling pattern also has no effect on the difficulty of its application. The ability to use anisotropy in predicting different marble parameters, and better understanding of confidence level values produced and how they can be associated with resource categories are considered for future work. More testing is also planned to investigate the influence of the grade field (when included as output) to domain predictions, and vice versa.

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