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学 位 論 文 内 容 の 要 旨

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学 位 論 文 題 名

Study on the Development of an AI-Based Mining Methods Recommendation System
(AI による採掘手法レコメンデーションシステム開発に関する研究)

Mining methods selection (MMS) is one of the most critical and complex decision-making tasks in mine planning. The MMS process aims to select the most feasible method(s) that maximises profits and recovery of mineral resources while minimising mining costs and environmental impacts. MMS has been studied for many years, culminating in the development of different MMS systems. The first MMS systems, termed qualitative systems, were introduced in the 1970s, which were essentially flowcharts that served as guidelines for selecting the most suitable surface and underground mining methods. The need for improvement led to the introduction of quantitative or numerical systems in the 1980s and 1990s, which continues to be one of the most used systems for MMS. Since the 2000s, attention has shifted to applying multi-criteria decision-making (MCDM) techniques in the MMS field to overcome the shortcomings of quantitative systems. Technological advancement, innovation and big data have led to the growth of artificial intelligence (AI) and its application in different fields of science and engineering. Recently, few studies have investigated the application of artificial neural network algorithms in MMS, thus proving their effectiveness in solving the complexity of the MMS process.

In light of improving and extending the application of AI, this research introduces the application of recommendation system technologies in the MMS discipline. Recommendation systems are part of AI systems aimed at recommending the most relevant items to users based on users' historical information. This research aims to develop an AI-based mining methods recommendation system (AI-MMRS) focusing on underground MMS. In order to develop the AI-MMRS, this research thus investigates the applicability of collaborative filtering (CF) recommendation systems, which generate recommendations based on interaction or similarities between users and items. As such, this research will evaluate the performance of two well-known CF approaches, memory-based and model-based. One objective is comprehensively understanding the most commonly implemented underground mining methods in the late 2000s.

The research database is based on mining projects' historical data collected from an open-source (sedar database) and the literature review. The research’s central concept is to use available mining project information to develop a system that will recommend the most appropriate mining methods by learning from previous mining projects' procedures. In the data preparation step, the MCDM Entropy method is applied for feature selection; to assess the relative importance of MMS influential factors and identify the most relevant factors. This research implements the memory-based CF approach using the k-nearest neighbours (KNN)-cosine similarity algorithm. Furthermore, the implementation of the model-based approach is done using the nonnegative matrix factorisation (NMF) algorithm and other machine learning (ML) classification algorithms namely KNN classifier, decision trees, support vector machines, kernel and artificial neural network. The NMF algorithm is mainly used as a first step for addressing data sparsity problems in the dataset, by predicting possible missing information in the dataset. The KNN-cosine similarity algorithm and the ML classification algorithms are used to train models for underground mining methods selection.

The results from the MCDM Entropy method suggest that ore strength, rock strength, orebody thickness, shape and dip are the most relevant influential factors in MMS. Therefore, these factors are the main variables or features

in the dataset used as input to train the models. The input dataset is composed of thirty-three case studies and seven different underground mining methods (i.e., block caving, cut and fill, room and pillar, longwall, shrinkage, sublevel caving and sublevel stoping). The performance of the algorithms is evaluated based on prediction and classification accuracy. The results prove the effectiveness of the NMF algorithm to predict missing values from a sparse dataset with an accuracy that ranges from 60 to 70 percent. Likewise, the accuracy of KNN-cosine similarity and most ML classification models ranges from 60-70 percent. In the machine learning (ML) world, the performance of the proposed models is considered moderated, not ideal; this is because most ML models are trained and optimized using large datasets (big data). However, in this case, the performance of the proposed models is seen as realistic considering the complexity of the MMS and the limited access to large mining projects' historical data.

The findings from this research suggest that the KNN-cosine similarity and the ML classification algorithms can be implemented on memory-based and model-based CF approaches, respectively. In addition, with the aid of NMF to predict missing values in the dataset, the AI-MMRS can be used even if some information about the input variables is not available. However, further investigations are necessary for optimizing the performance of the models by continuously collecting data, training, and optimizing the models.

Mining methods selection (MMS) is considered complex owing to the need to consider several input factors, including the orebody geometry, geology, geotechnical properties, and technological, economic, and environmental factors. Underground MMS is considered the most complicated owing to the complexity associated with the orebody geometry, geology, and geotechnical properties. Usually, the first step of MMS consists of selecting a set of most feasible mining methods based on orebody geometry, geology and geotechnical properties which are submitted for further investigations (including technological, economic, and environmental factors). The outcome of this research proves the applicability of CF algorithms to develop the AI-MMRS based on orebody geometry (i.e., thickness, shape, and dip) and geotechnical properties (i.e., ore strength, host rock strength). The AI-MMRS can be practically implemented during the first stage of underground MMS to recommend a set of mining methods that will then be submitted for economic, technological, environmental, and political analysis during the mine planning process.

Abbreviations

AI: Artificial intelligence

AI-MMRS: Artificial intelligence-based mining methods recommendation system

MMS: Mining methods selection

MCDM: Multi-criteria decision-making

CF: Collaborative filtering

ML: Machine learning

KNN: k-nearest neighbours

NMF: Nonnegative matrix factorisation