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Editorial

Introduction to the Special Issue "Advances in Computational Intelligence Applications in the Mining Industry"

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This is an exciting time for the mining industry, as it is on the cusp of a change in efficiency as it gets better at leveraging data. After decades of focusing on collecting data, the industry has developed to where the focus now is on utilizing the data. The utilization of data typically involves developing models that are used to better understand mining processes, with a variety of computational intelligence (CI) techniques being at the forefront of methods used to develop models. Modeling and data collection add value by presenting analytics so that humans, from frontline workers to corporate executives, can respond as quickly as possible to changing conditions.

CI is often defined as a class of techniques, which includes neural networks, fuzzy systems, and evolutionary computing. Many papers in this issue make excellent use of these techniques to advance the state of the industry. However, given the broad nature of the mining industry, we also chose to include other data-driven computational techniques that are advancing the state of the art, regardless of whether they fall directly under CI. Our focus was more on capturing the advances than maintaining the purity of the techniques.

The papers in this issue advance the state of the art in four broad categories: mine operations, mine planning, mine safety, and advancing the sciences, primarily in image processing applications. In the field of mining operations, Both and Dimitrakopolous [1] utilize drill hole penetration rates to predict ball mill throughput. They combine a variety of techniques, including neural networks, in their work. Young and Rogers [2] acknowledge the important role stockpiles play in managing ore that is supplied to the mill, and the industry's struggle in understanding the grade distribution within the stockpiles. They demonstrate that data from mine dispatch systems can be combined with traditional interpolation techniques to obtain the grade distribution of stockpiles. Olivier and Aldrich [3] similarly show the value of combining simplicity with operational data. They extract control rules from semi-autogenous grinding (SAG) mill operational data using decision trees. In controlling the mill for power draw, the decision trees identify the same factors as important as random forests.

In the field of mine planning, authors have either leveraged existing mine plans or offered methods to improve mine plans. At a Mongolian mine, Sarantsatsral et al. [4] use random forests to predict rock types in various mine planning scenarios. They determine that rock types could be predicted relatively well for some mine planning scenarios. de Carvalho and Dimitrakopoulos [5] improve real-time truck dispatch decisions by basing them on a deep Q-learning reinforcement neural network model. The reinforcement model is trained based on a continuous real-time discrete event simulation (DES) model, which simulates short-term mine plans. Wilson et al. [6] utilize partial least squares (PLS) regressions to model the geological uncertainty in oil-sands. They combine the PLS models with DES methods to stabilize plant throughput, despite uncertainties in geology and processing methods. Park et al. [7] leverage the Internet of Things to collect truck travel times and environmental data from the transportation systems at a limestone mine. They apply various machine learning models to identify when the transportation system suffered

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bottlenecks. The models are then used to anticipate problems in the transportation system, aiding production planning.

Three diverse papers related to mining health and safety are included in this Special Issue. Talebi et al. [8] explore the complex problem of mine operator fatigue using computational intelligence. The authors use a random forest model with operational technology data and a PERCLOS fatigue monitoring system. The model identifies some interesting leading indicators of fatigue found in operational technology. Many health and safety management systems (HSMSs) are dependent upon qualitative/narrative datasets. Ganguli et al. [9] explore using natural language processing (NLP) to contextualize these datasets. The authors use large US-based MSHA datasets to train NLP models. These models can then be used to improve the analysis of HSMS data at mine sites. Mining companies strive to reduce risk to their operations and surrounding stakeholders. Chomacki et al. [10] explore methods to improve the understating of mining impacts on local stakeholders. Two models are created to assess risk to surface buildings from underground mining units of operation. These tools will help manage the complex risks of mining impacts on proximity stakeholders.

Five papers were included in the Special Issue that utilizes computational intelligence tools to advance fundamental science in the areas of prospectivity mapping, rock/ore classification, and rock fragmentation. First, Lachaud et al. [11] present a data-driven mineral prospectivity model to identify areas with higher discovery potential. They use existing geological datasets to train random forest machine learning models to improve exploration decisions. Next, Sinaice et al. [12] present a model to help mining companies more quickly classify rock masses using hyperspectral imaging, neighborhood component analysis, and machine learning. By integrating these computational tools, the authors present a rock mass classification model that can quickly and accurately predict geological properties. Advanced imaging technologies are changing geological sampling and analysis. Iwaszenko and Róg [13] provide an image analysis model to segment important geological features of coal. The modeling can speed up the analysis, thereby influencing key mineral processing decisions and earlier capturing valuable time and energy.

In addition to the image analysis discussed, Tungul et al. [14] provide an updated approach to simplifying fragmentation analysis using smartphones and GNSS technology. The authors showcase a methodology that can reduce the inherent error of GNSS. The methodology can reduce the cost of fragmentation analysis and improve the speed of analysis. This has the potential to allow smaller operations access to this critical mining and mineral processing variable. Along the lines of rock fragmentation computational intelligence, Dumakor-Dupey et al. [15] provide a review of computational intelligence and blast-induced impacts. The authors explore various blast-impact empirical and machine learning models. The paper provides a guide for future research in this area.

The editors are pleased with the results of the Special Issue and appreciate the contributions of the authors, which include important contributions to computational intelligence and operational excellence. In addition, the contributions to advancing fundamental science in the mining domain will yield important results in the future. Digital transformation's benefits rest on computational intelligence and a culture of process change around analytics. The mining and minerals industry, academia, and governments need to continue to invest in research and development in this area. The research presented in this Special Issue is an important, albeit small, contribution to this endeavor.

Conflicts of Interest: The authors declare no conflict of interest.

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