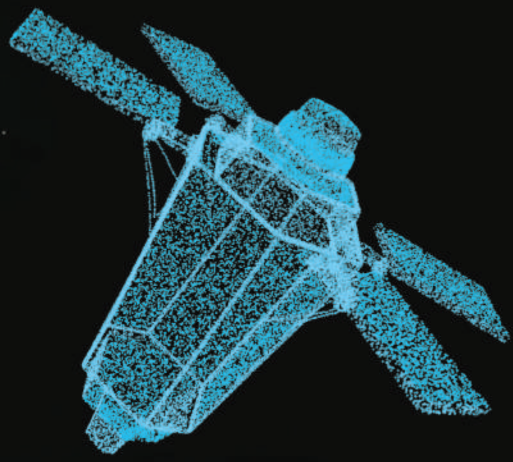
26th World Mining Congress

BRISBANE AUSTRALIA
26–29 JUNE 2023



Resourcing Tomorrow

Creating Value for Society

Proceedings

HOSTED BY

CSIRO

WMC2023.ORG

The WMC 2023 program looks to the future of mining and resources in a global context. Themes will be addressed in plenary and concurrent sessions, special interest group meetings, workshops and discussion panels. The focus is on active participation, giving attendees opportunities to present and participate in important discussions on the major current and future issues and challenges facing mining and resources across the globe.

This structure will allow delegates to take "deep dives" into the latest developments and new research in these specific areas. These parallel streams will be interspersed with joint-stream and plenary sessions where delegates come together to explore nexus issues.

The Congress will explain and explore how technology is transforming the sustainable production of minerals and fuels creating value that continues to lift significant segments of the world's population out of poverty and contributes in an essential manner to an improved way of life.

Published by the 26th World Mining Congress (WMC 2023)

ISBN: 978-0-646-87565-1

We acknowledge the Traditional Owners of the lands and waters throughout Australia, and pay respect to the Elders past, present and emerging. We recognise the importance of connection to culture, land, kinship and community to the health and wellbeing of Aboriginal & Torres Strait Islander families. We acknowledge the cultural practices and traditions still carried out today and being passed down to future generations.

Development of Machine Learning Models using IES-ModelNet application for fast simulation of operation response to blocks of the resource block model

Eiman Amini[a], Edwin J. Y. Koh[a,b], Miguel Becerra[c], Christian Jara[d], Nick Beaton[a]

[a] *Orica Digital Solution, Brisbane, Queensland, 4069*
[b] *School of Mathematics and Physics, University of Queensland, Brisbane, Queensland, 4072*
[c] *Teck Resources, Latin America Group, Santiago, Chile.*
[d] *Teck Resources, Carmen de Andecollo, Chile.*

ABSTRACT

Using phenomenological models of individual unit operations is a common practice to model and optimise mineral processing plants over Life of Mine (LOM). Therefore, millions of simulations are required to assess all possible process configurations and scenarios for an operation's LOM using the block model. The number of simulations even increases if the ore variability and uncertainty of the ore characterisation test work is added to the analysis. Meta or Surrogate model development is an engineering machine learning approach which approximates the outcomes of one or multiples of inter-linked underlying models which requires much less computation power therefore more feasible. Neural networks are suitable option for development of the MetaModels because of their flexibility and capability to approximate simple or complicated functions regardless of the number of inputs/outputs.

A MetaModel was developed based on an Integrated Extraction Simulator (IES) flowsheet that contained several crushing and grinding equipment models such as multi-stage crushing units, HPGR, SAG and ball mills in the flowsheet. The MetaModel was trained based on IES simulation of a small portion of the blocks selected from the block model to represent the entire range of ore properties in the block model such as grindability parameters. The MetaModel could predict the throughput with 0.45% error and 306633 times faster than phenological models. The development process required a stratified training sample of 1 in 1000 data from the block model.

KEYWORDS

Machine Learning, Simulation, MetaModel, Comminution, Neural Networks, Process Modelling.

1 Introduction

Various processing configurations, mine schedules, and process scenarios are evaluated to maximise process efficiency and value can be generated from a resource. This requires evaluation of all possible scenarios to run a mine value chain which results in millions of simulations of the resource model to determine the optimal mining and processing strategies. Multiple phenomenological models are usually used in simulations as they contain physical fundamentals which helps for interpretability and extrapolation. Modelling and simulations using multiple phenomenological models together demands solver-based techniques which are computationally intensive. Also, optimising the entire operation or a process design is an iterative process as more conditions at increasing resolution of variables are explored, the number of required simulations easily increases to the order of millions (Amini et al., 2020).

In industry, it is common to perform simulations through specialised commercial software like METSIM (Bartlett et al., 2014), MODSIM (Ford & King, 1984), USIM PAC (Durance et al., 1994), SysCAD (Razavimaneseh et al., 2006), CEET (Kosick et al., 2001) and FLEET (Dobby et al., 2002), JKSimMet (Morrison & Richardson, 2002), JKSimFloat (Harris et al., 2002), or through proprietary equations set up in Microsoft Excel sheets. These were done on a local computer and limited to a magnitude of thousands of simulations in a long period of time due to hardware limitations and lack of fully automated process. This is also due to the use of solver-based algorithms to solve simultaneous equations to find local minima. To overcome this issue, the Cooperative Research Centre for Optimising Resource Extraction (CRC ORE) developed cloud-based simulation software known as the Integration Extraction Simulator (IES) which was commercialised by Orica. IES can integrate the process constraints of the site in the simulations to predict the plant best behaviour. Amini, et al. (2020) showed the optimisation of the comminution circuit through 14 million simulations of phenomenological models within a week. Although feasible, this "brute-force" solution is costly if the millions of simulations are to be repeated with block model variations or updates. Therefore, there is a common desire for an alternative approach to reduce the simulation time to fully explore the different mine schedules, process configuration, and block model variations.

Development of MetaModels were considered to speed-up the process. Meta or Surrogate model development is an engineering machine learning approach which approximates the outcomes of one or multiples of inter-linked underlying models which requires much less computation power therefore more feasible. MetaModels can be used in process engineering to approximate a chemical system or process for optimisation simulation according to McBride and Sundmacher (McBride & Sundmacher, 2019). Application of MetaModels in minerals processing were only found on simplifying CFD unit models in flotation (Rabhi et al., 2018), thickening (Stephens et al., 2011; Stephens & Fawell, 2012), and pharmaceutical milling (Metta et al., 2020). Koh et al., (2022) just recently developed MetaModel for minerals processing to approximate a minerals processing comminution circuit.

Neural networks are suitable option for development of the MetaModels because of their flexibility and capability to approximate simple or complicated functions regardless of the number of inputs/outputs. The most basic form of neural networks is the multi-layer perceptron (MLP) which is a dense feed-forward neural network (Almeida, 1997) shown in Figure 1.

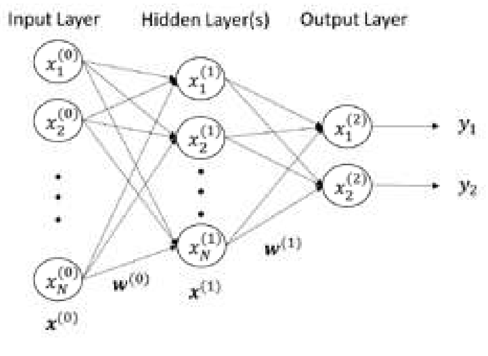


***Figure 1** – Feed-forward neural network (multi-layer perceptron) with one hidden layer. Note that the number of neurons in each layer, N does not have to be equal.*

 ISBN: 978-0-646-87565-1

The neural network consists of non-linear activation functions which provides its non-linear approximation capability (Hornik, 1989). Furthermore, neural networks can be represented as matrix operations which benefit from parallel computing. Neural networks are ultimately flexible empirical models which do not inherently capture underlying physical mechanisms. McCoy & Auret (2019) provides an extensive review of the existing attempts of using machine learning models in minerals processing. In their review, majority of neural networks developed in mineral processing are small in structure due to the lack of data. However, with proper care in sampling and experimental design for the training data, this study demonstrates that the physical behaviour of models can be approximated with good accuracy.

This study focuses on development of a novel methodology to use MetaModels for approximation of all the integrated phenomenological process models in an IES comminution circuit to significantly reduce required time for mass simulation of a resource block model to assess several operation scenarios.

2 Methodology

2.1 IES flowsheet

An IES flowsheet was developed to simulate the performance of Carmen de Andacollo (CdA) copper operation value chain by collaboration between Orica Digital Solution and Teck Resources Chile. The flowsheet then used to assess the impact of new blast designs and addition of a HPGR to the crushing circuit on the production rate.

Figure 2 shows the flowsheet developed based on the CdA circuit represented by phenomenological production unit models in IES. The flowsheet consists of four blasting domains, four crushing circuits including the 5 kilo ton per day mobile crusher, SAG and ball milling circuits and flotation process. The flotation process model was developed using Machine Learning (ML) techniques. The development of the flotation model is explained in detail by Koh et. al. (2022).

A small sample of block model was selected for simulations using the IES flowsheet to develop and test the MetModel.

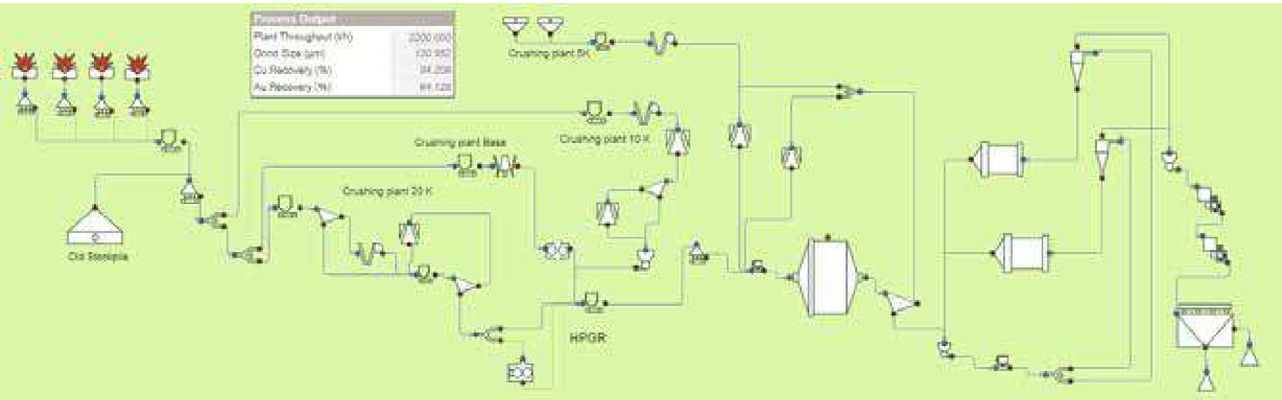


Figure 2 *– Flowsheet summary in IES of the comminution circuit of the Carmen de Andacollo*

 ISBN: 978-0-646-87565-1

Figure 3 summarises the entire process of developing the MetaModel used in this paper.

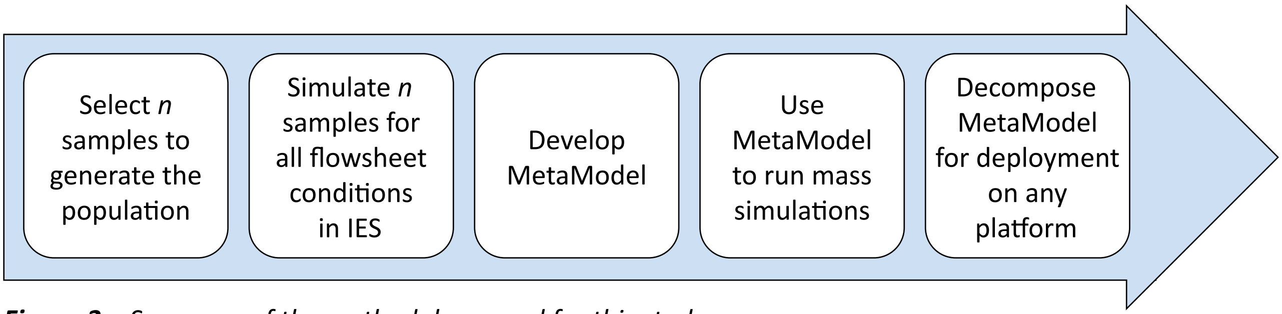


***Figure 3** – Summary of the methodology used for this study.*

Selection of *n* samples from the resource block model was done to generalise the ore properties such as hardness is the first step in development of a MetaModel. Once the *n* samples from the block model is selected, the IES simulations are run on those for the given operating conditions. The input parameters to the IES flowsheet and the outputs are used to train a MetaModel. It should be noted, if the number of operating scenarios changes, the optimal MetaModel hyperparameters needs to be adjusted accordingly. Eventually, the MetaModel is used to simulate the selected blocks of the blocks for the given scenarios which is compared to the IES simulations conducted on the same data set under the same scenario conditions. After the desirable quality of simulation is achieved the MetaModel is deployed to be used on a platform.

2.2 Hardware and Software

The software used in this study was Python 3.7.9 64-bit, Keras 2.3.1 (Chollet, 2015) and Tensorflow 2.0.0 Central Processing Unit (CPU) backend. The hardware was a 8-core Intel i7-9700 CPU chip and 32GB of RAM.

2.3 Neural Network model training

As mentioned earlier a Neural Network was trained based on the selected IES simulation result to create the CdA flowsheet MetaModel. The selected data are divided into three groups of training, validation and test data sets. Training and validation data sets are used to develop the Neural Network model to avoiding overfitting. The test data set is used at the end of the process as a 'blind' test to make sure the neural network accuracy and precision is acceptable.

3 Results

The result of the developed MetaModel process for the CdA is demonstrated and compared with the IES flowsheet simulations to quantify the fidelity of the MetaModel in this section.

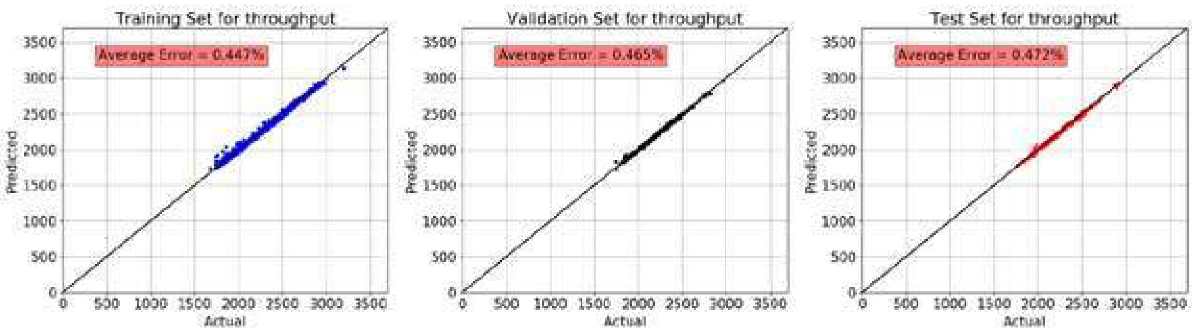


***Figure 4** – Parity chart of the neural network prediction against the IES simulations for throughput for test (blue), validation (black) and test (red).*

 ISBN: 978-0-646-87565-1

IES simulations were done on 5292 blocks for two levels of blast intensity for four domains at CdA pit. The simulations were done with and without the HPGR unit in the crusher circuit. Figure 4 shows the parity chart of the neural network prediction against the phenomenological model results for training, validation and test data sets. The average relative error for the test data set is 0.472% and lower than the round-off error. The round-off error is 20 tph for the throughput simulations in IES. Figure 5 shows the histogram of relative error distribution in the IES and MetaModel comparison which indicates only 6.9% of the predictions have errors above 1%.

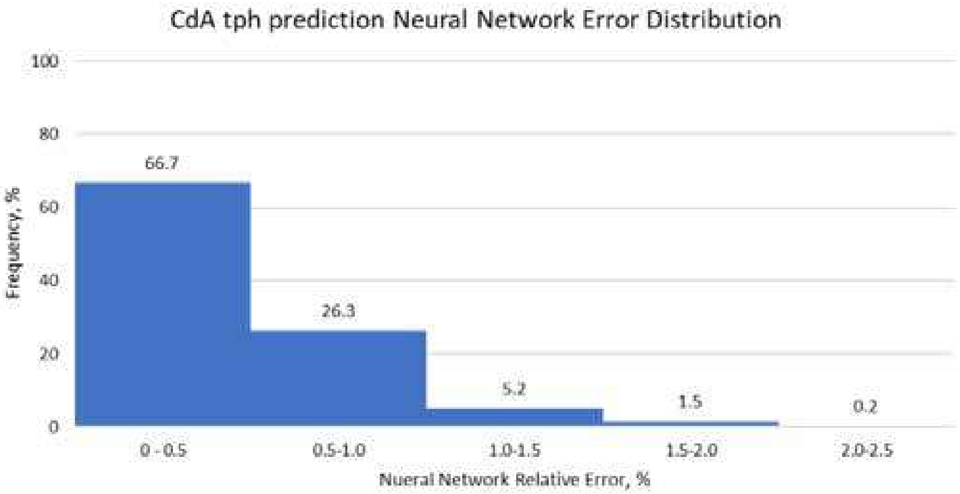


Figure 5 *– Histogram of error distribution according to the operating strategies.*

The flotation model developed for the CdA flowsheet is a Neural Network model based on 980 days of historical data, therefore the simulations in IES and MetalModel is the same.

4 Discussion

The test results show that sampling a small fraction (approximately 1/1000) of the block model is possible to interpolate the entire block model at a cost of slightly reduced accuracy. The solver-based solutions of throughput have a convergence threshold of 20 t/h which is around 0.66% for a throughput of 3000 t/h. Therefore, MetaModel solutions with errors below 0.66% is indistinguishable from the phenomenological model solutions due to round-off errors. Given that the average error of the entire MetaModel results is 0.45%, this is well within the acceptable limits for simulation purposes. This is especially true for minerals processing modelling and simulations where the accuracy of input data/sensors are greater but only the mathematical error between the original simulations and the MetaModel results are reported here which is expected to be less than round-off error.

Significant care was taken in the methodology to minimise overfitting of the final MetaModel. The main reason overfitting occurs in neural network development is the training dataset is usually much larger than the test dataset. In this study the contrast is true, and the computational speed-up is more apparent as the training dataset becomes smaller. As a result, test set 1 is 1000 times larger than the training dataset which makes overfitting impossible.

The benefit of using a neural network MetaModel is very clear as it greatly reduces computational cost and time required at negligible loss in accuracy. The MetaModel could predict throughput with 0.45% error and 306633 times faster than phenological models. This will also allow the exploration of mine conditions at a larger scale which was constraint to time and budget before. However, phenomenological models are still required to generate the training data for the neural network albeit at times less.

5 Conclusion

This study investigated the possibility of using a neural network as a MetaModel to approximate phenomenological models to improve the number of simulations possible per second. The block model of a large copper porphyry mine was analysed to determine the number of representative blocks required to interpolate the entire block model. Through heuristics and expert analysis, it was determined that the blocks can be sampled according to groups hardness and head grade properties. A sampling ratio of approximately 1:1000 was adequate which means only a small fraction of blocks was required to generalise the entire block model region for each given flowsheet condition.

A total of 16 scenarios was used, yielding a training dataset of 5292 blocks. The MetaModel algorithm took few hours to search and found the best architecture and get trained. The MetaModel could predict throughput with 0.45% error and 306633 times faster than phenological models. The entire methodology has been designed to be automated based on the block model input except for the block model sampling procedure. The methodology can be repeated automatically for any changes in the block model or simulation of other mine operation value chains. The neural network can approximate phenomenological models at a small cost of accuracy but greatly reduced the time required for simulations.

References

Almeida, L. B., 1997. Multilayer perceptrons. In: Fiesler, E., Beale, R. (Eds.), Handbook of Neural Computation. New York: IOP Publishing Ltd.

Amini, E., Becerra, M., Bachmann, T., Beaton, N., Shapland, G., 2020. Development and Fine-tuning of a Mine Operation Value Chain Flowsheet in IES to Enable Grade Engineering and Process Mass Simulations for Scale-Up and Strategic Planning Analysis. Society for Mining, Metallurgy and Exploration Annual Conference.

Bartlett, J., Holtzapple, A., Rempel, C., 2014. A Brief Overview of the Process Modelling/Simulation and Design Capabilities of METSIM. Canadian Institute of Mining, Metallurgy and Petroleum: COM 2014 - Conference of Metallurgists Proceedings.

Chollet, F., 2015. Keras. Retrieved from GitHub repository: https://github.com/fchollet/keras

Dobby, G., Kosick, G., Amelunxen, R. (2002). A focus on variability within the orebody for improved design of flotation plants. Ottawa, Ontario: 34th Annual Canadian Mineral Processing Conference.

Durance, M.-V., Guillaneau, J.-C., Villeneuve, J., Brochot, S., Fourniguet, G., 1994. USIM PAC 2 for Windows: Advanced simulation of mineral processes. Cappadocia, Turkey: Proceedings of the 5th International Mineral Processing Symposium.

Ford, M. A., King, R. P., 1984. The Simulation of Ore-Dressing Plants. International Journal of Mineral Processing, 12, 285-304.

Harris, M. C., Runge, K. C., Whiten, W. J., Morrison, R. D., 2002. JKSimFloat as a practical tool for flotation process design and optimisation. Mineral Processing Plant Design Practice and Control Conference. New York, USA: Society for Mining Metallurgy & Exploration.

Hornik, K., 1989. Multilayer Feedforward Networks are Universal Approximators. Neural Networks, 2, 359-366.

Koh, E., Amini E., Gaura S., Becerra Maquieirac M., Jara Heck, C., McLachlan G., Beaton N. 2022. An Automated

 ISBN: 978-0-646-87565-1

Machine learning (AutoML) approach to regression models in minerals processing with case studies of developing industrial comminution and flotation models. Minerals Engineering 189 (2022) 107886.

Kosick, G., Dobby, G., Bennett, C., 2001. CEET (Comminution Economic Evaluation Tool) (For Comminution Circuit Design And Production Planning). Denver, Colorado, USA: Proceedings of 2001 SME Annual Meeting.

McBride, K., Sundmacher, K., 2019. Overview of Surrogate Modelling in Chemical Process Engineering. Chemie Ingenieur Technik, 91(3), 228-239.

McCoy, J. T., Auret, L., 2019. Machine learning applications in minerals processing: A review. Minerals Engineering, 132, 95-109.

Metta, N., Ramachandran, R., Ierapetritou, M. A., 2020. A Computationally Efficient Surrogate-Based Reduction of a Multiscale Comill Process Model. Journal of Pharmaceutical Innovation, 15, 424-444.

Morrison, R. D., Richardson, J. M., 2002. JKSimMet: A simulator for analysis, optimisation and design of comminution circuits. Mineral Processing Plant Design Practice and Control (pp. 442-460). New York, USA: SME: Society for Mining, Metallurgy and Exploration.

Rabhi, A., Chkifa, A., Benjelloun, S., Latifi, A., 2018. Surrogate-based modelling in flotation processes. Computer Aided Chemical Engineering, 43, 229-234.

Razavimaneseh, A., Rumball, J., Tadel, M., & Pareek, V., 2006. Steady-state simulation of hybrid nickel leaching circuit using SysCAD. Auckland, New Zealand: Chemeca 2006: Knowledge and Innovation.

Stephens, D. W., Gorissen, D., Crombecq, K., & Dhaene, T., 2011. Surrogate based sensitivity analysis of process equipment. Applied Mathematical Modelling, 35, 1676-1687.

Stephens, D., & Fawell, P., 2012. Optimization of Process Equipment Using Global Surrogate Models. Melbourne, Australia: Proceedings of the Conference on CFD in the Minerals and Process Industries CSIRO.

ISBN: 978-0-646-87565-1