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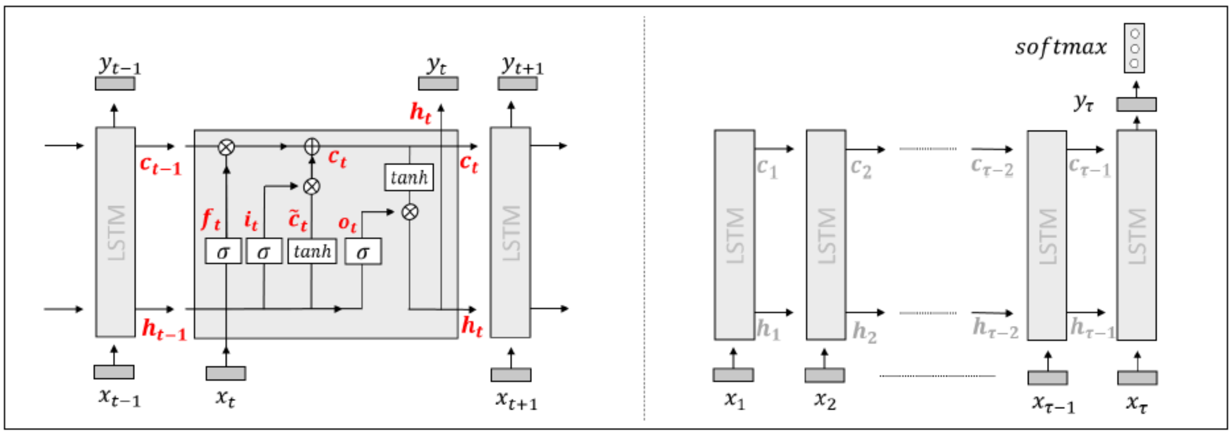
An LSTM Approach for SAG Mill Operational Relative-Hardness Prediction



Introduction

Optimization of ore processing equipment in mining, especially comminution, is an important task. Since too much of the energy goes toward comminution in the whole mining process, this increases its importance. One such process wherein the efficiency of semi-autogenous grinding (SAG) mills goes a long way is the extraction of minerals from ore. SAG mills are located at the front end of grinding circuits and represent grinding by impact, abrasion, and attrition combined, which makes up more than half of the energy consumed in any mine. These are very big (12.8 m by 7.6 m are typical dimensions) and energy-hungry machines-potentially ranging from 8.2 to 26 MW-and are central to any mining operation.

Methodology

The concept of ORH and the architecture of the neural network are discussed here.

- ORH Framework: ORH is a qualitative measure whereas other measures of hardness are inherently quantitative measures relying on a number of attributes of an ore sample. In the context of the SAG mill, ORH could be driven simply by variations in energy consumption (EC) and feed tonnage (FT). ORH categorization occurs in three forms—soft, hard, and undefined—and is established based on the deviations of energy and tonnage over time.

  For instance:

  1. If energy increases with stable tonnage, then the ORH is probably "hard."
  2. If energy drops with stable tonnage, it might be called "soft."
  3. If both variables change in parallel, which is both increase or decrease, then the ORH is considered "undefined," because such trends may simply indicate changes in mill filling rather than hardness.

- LSTM Network: An LSTM is a specific type of RNN designed specifically for time-series prediction. The beauty of LSTM lies in its ability to learn long-term dependencies among data sequences. For ORH predictions, past operational data sequences are important in determining the future properties of ore.

  Some important components of LSTM are as follows:

  1. Forget Gate: It determines what information should be preserved from previous states.
  2. Input Gate: It brings in essential new information.

3. Output Gate: Outputs the final prediction for the timestep.

The LSTM model employs historical half-hour data intervals to predict ORH at various time horizons forward such as 0.5, 2, and 8 hours.

Dataset and Experimental Setup

The dataset for this work was sourced from SAG mill operations at half-hourly resolutions covering nearly a year long term. Each entry in the data has provided critical information on operational parameters:

- Feed Tonnage (FT): The ore feeds into the mill in tons per hour.
- Energy Consumption (EC): Kilowatt-hours that vary with hardness of the ore
- Bearing Pressure (BPr) and Spindle Speed (SSp): Indicators of the internal states of the mill, providing some feeling of the state of the operation of the mill.

For performance stability across various conditions, the dataset was split between training and testing sets, approximately about half each.

- Preprocessing: Normalization was achieved for each through calculation of mean and standard deviation on the training data set. The model further utilized trend features which calculated differences of EC and FT from one point to another to denote dynamic changes going on in ORH. Each and every instance of each category under the term "ORH" was described in one-hot encoding, converting "soft," "hard," or "undefined" into more streamlined forms for the model to interpret.

- Experiment Configuration: The model was run at a number of time supports, including 0.5, 2, and 8 hours, while different sensitivities in the classification of ORH are controlled by varying lambda (λ) values. The purpose of this experiment is to find an appropriate trade-off between sensitivity and prediction accuracy.

Model Design and Parameters

The architecture as well as the input structure of the LSTM model, along with parameters optimized for best prediction of ORH, is discussed in this section.

- Feature Selection: Five input variables were selected: feed tonnage (FT), bearing pressure (BPr), spindle speed (SSp), and the incremental changes in FT and SSp. While including absolute and differential values allows the model to spot current states and recent trends, it also shows accuracy in predictions.

- Temporal Window: Since it is four hours with equivalent eight data points, a model can recognize temporal dependencies. This window size gives the LSTM the ability to learn effects both in short-term and long-term influences that are necessary for actually making ORH predictions.

- Hyperparameters: With the results of past studies and some experimental optimizations, the LSTM model applies between 240 and 596 hidden units depending on the dataset and time support. Further, the Adam optimizer is used in the optimization process to learn the best of the models with a set of hyperparameters tuned for this dataset.

Observations and Results

The results will illustrate the accuracy achieved by the model at various values of λ and time supports.

- Accuracy and λ Sensitivity: When λ was increased, the precision of ORH predictions got better. This also opened up the range for "constant" classification and lessened both hard and soft labels. For example, When **λ = 0.5**, it managed to have **77%** accuracy in predicting **0.5** hours, whereas it dropped to **52%** at 8 hours.When λ is risen to **1.5**, then it is further enhanced up to **93%** for **0.5** hour predictions, and close to **80%** for 8-hour predictions.
- Confusion Matrices: The confusion matrices demonstrate the ability of the model to avoid extreme misclassifications, such as marking a "soft" as "hard". The extreme misclassification rates at **0.5** hours time support remain near **1%** for both of the SAG mills, showing that the LSTM model is able to distinguish between the "soft" and "hard" categories of the ORH.

- Time Horizon: The model works best at the shortest time horizon (.5-hour). Accuracy falls off with longer time horizons since it is much harder to generalize over longer periods. This trade-off may still meet operational objectives for short-time and long-time planning.

- Below is the image showing the generated dataset for SAG mill 1. It has both the training and test dataset.

```
Training Data Sample:
   Feed Tonnage  Energy Consumption  Bearing Pressure  Spindle Speed
0   1157.866934         9250.441565         12.373984       9.945931
1    842.282642        11500.500644         13.700000       8.381895
2   1232.901203        10253.816099         11.717923       9.399841
3   1667.945839         8950.715996         13.700000       8.129689
4    794.625773         9340.909902         10.926071       9.505450

Testing Data Sample:
   Feed Tonnage  Energy Consumption  Bearing Pressure  Spindle Speed
0    728.189816         9530.216204         11.759309      10.700000
1    896.290954         9382.970278         11.692695       9.631884
2   1401.492867         8574.693587         11.155849       8.756315
3   1617.965536        10737.814139         12.381456       9.403334
4    957.479483         8447.013159         13.700000       9.412891
```

- Training for 20 epochs and the corresponding RMSE for SAG mill 1 is as follows

```
Epoch 1/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 25s 81ms/step - loss: 0.0635 - val_loss: 0.0485
Epoch 2/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 78ms/step - loss: 0.0539 - val_loss: 0.0480
Epoch 3/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 19s 74ms/step - loss: 0.0533 - val_loss: 0.0478
Epoch 4/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 21s 78ms/step - loss: 0.0536 - val_loss: 0.0476
Epoch 5/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 76ms/step - loss: 0.0528 - val_loss: 0.0476
Epoch 6/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 74ms/step - loss: 0.0546 - val_loss: 0.0476
Epoch 7/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 77ms/step - loss: 0.0538 - val_loss: 0.0478
Epoch 8/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 18s 72ms/step - loss: 0.0543 - val_loss: 0.0475
Epoch 9/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 22s 77ms/step - loss: 0.0523 - val_loss: 0.0476
Epoch 10/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 74ms/step - loss: 0.0528 - val_loss: 0.0475
Epoch 11/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 21s 77ms/step - loss: 0.0520 - val_loss: 0.0537
Epoch 12/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 19s 75ms/step - loss: 0.0534 - val_loss: 0.0476
Epoch 13/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 22s 81ms/step - loss: 0.0513 - val_loss: 0.0475
Epoch 14/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 39s 73ms/step - loss: 0.0526 - val_loss: 0.0495
Epoch 15/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 79ms/step - loss: 0.0514 - val_loss: 0.0476
Epoch 16/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 18s 73ms/step - loss: 0.0520 - val_loss: 0.0480
Epoch 17/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 19s 75ms/step - loss: 0.0526 - val_loss: 0.0480
Epoch 18/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 20s 73ms/step - loss: 0.0533 - val_loss: 0.0475
Epoch 19/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 19s 73ms/step - loss: 0.0526 - val_loss: 0.0475
Epoch 20/20
254/254 ━━━━━━━━━━━━━━━━━━━━ 21s 76ms/step - loss: 0.0532 - val_loss: 0.0480
254/254 ━━━━━━━━━━━━━━━━━━━━ 5s 17ms/step
Root Mean Squared Error: 462.3408027459843
```

- Below is the image showing the generated dataset for SAG mill 2. It has both the training and test dataset.

Training Data Sample:

	Feed Tonnage	Energy Consumption	Bearing Pressure	Spindle Speed
0	2641.267278	14618.770665	18.300000	9.134790
1	1919.931754	18742.467206	13.088456	8.372371
2	2812.774179	19688.000000	17.956571	9.640519
3	3477.000000	16646.962814	13.276117	9.027734
4	1811.001766	19688.000000	10.413203	9.314693

Testing Data Sample:

	Feed Tonnage	Energy Consumption	Bearing Pressure	Spindle Speed
0	2049.582320	17496.794775	17.502233	9.069949
1	2224.663916	19064.733808	9.518411	8.189657
2	2271.120742	15560.776572	10.104824	9.312769
3	2450.534370	19489.601785	12.921962	8.942867
4	985.443336	19224.523348	17.868701	8.954133

- Training for 20 epochs and the corresponding RMSE for SAG mill 2 is as follows

```
247/247 ━━━━━━━━━━━━━━━━━━━━ 34s 106ms/step - loss: 0.1053 - val_loss: 0.0831
Epoch 2/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 33s 75ms/step - loss: 0.0856 - val_loss: 0.0849
Epoch 3/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 19s 77ms/step - loss: 0.0856 - val_loss: 0.0824
Epoch 4/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 79ms/step - loss: 0.0828 - val_loss: 0.0868
Epoch 5/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 19s 76ms/step - loss: 0.0831 - val_loss: 0.0837
Epoch 6/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 21s 84ms/step - loss: 0.0856 - val_loss: 0.0829
Epoch 7/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 19s 75ms/step - loss: 0.0859 - val_loss: 0.0829
Epoch 8/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 21s 84ms/step - loss: 0.0826 - val_loss: 0.0823
Epoch 9/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 80ms/step - loss: 0.0848 - val_loss: 0.0826
Epoch 10/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 19s 74ms/step - loss: 0.0826 - val_loss: 0.0823
Epoch 11/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 21s 75ms/step - loss: 0.0831 - val_loss: 0.0823
Epoch 12/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 74ms/step - loss: 0.0835 - val_loss: 0.0823
Epoch 13/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 18s 74ms/step - loss: 0.0846 - val_loss: 0.0828
Epoch 14/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 21s 76ms/step - loss: 0.0839 - val_loss: 0.0842
Epoch 15/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 74ms/step - loss: 0.0827 - val_loss: 0.0823
Epoch 16/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 73ms/step - loss: 0.0834 - val_loss: 0.0825
Epoch 17/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 21s 75ms/step - loss: 0.0824 - val_loss: 0.0823
Epoch 18/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 73ms/step - loss: 0.0830 - val_loss: 0.0824
Epoch 19/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 21s 76ms/step - loss: 0.0847 - val_loss: 0.0823
Epoch 20/20
247/247 ━━━━━━━━━━━━━━━━━━━━ 20s 74ms/step - loss: 0.0837 - val_loss: 0.0823
247/247 ━━━━━━━━━━━━━━━━━━━━ 5s 19ms/step
Root Mean Squared Error: 997.2364758823867
```

Conclusion and Implications

The study confirmed that an LSTM approach to predicting the ORH of SAG mills presents good accuracy, especially in terms of the shortening of the time supports. This method is data-driven, offering a realistic, alternative alternative for the estimation of ore hardness using only operational variables, derived from sources easier and faster to obtain than direct geological inputs.

- Key Contributions : The performances of the proposed LSTM model in real-time mining operations demonstrate the possibility of machine learning in accurate, dynamic real-time predictions for supporting better decisions in SAG mill settings. The real-time ORH forecasting will enable operators to adjust the mill settings proactively and optimize energy efficiency and overall performance.

- Broader Impact: the prediction model ORH can be integrated with monitoring digital platforms in order to provide on-line feedback to SAG mill operators. This method, considering its nature, is most probably applicable for any other grinding and crushing equipment when operational conditions data become available.

Reference

- An LSTM Approach for SAG Mill Operational Relative-Hardness Prediction
- Colab Notebook