

Developing Deep Learning Based Intelligent Perception Algorithm for Thickener Equipment Monitoring

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Abstract

Dense dehydration by use of thickener equipment is a critical process in mineral processing, directly impacting the quality of concentrate products. However, current industrial practices lack effective methods for monitoring the condition of thickeners. This makes it difficult for operators to accurately perceive the internal state of the thickener, leading to a relatively inefficient production process. This paper addresses the challenge of real-time detection of one of the key process parameters, feed rate, in thickener by employing a data-driven model-ing approach with intelligent perception. The upstream processes are analyzed, and relevant variables are selected for modeling. The Long Short-Term Memory (LSTM) - Recurrent Neural Network (RNN) and the Gated Recurrent Unit (GRU) - RNN with the Particle Swarm Optimization (PSO) algorithm are used to build and train the models. The results show that the PSO-GRU-based intelligent perception model for thickener feed rate estimation achieves higher accuracy and shorter training times compared with the LSTM-RNN model.

Keywords

intelligent perception, deep learning, LSTM-RNN, GRU-PSO, thickener

1. Introduction

Mineral processing is a crucial and indispensable step after geological exploration and mining, and before metallurgical or chemical processing in many material production value chains. It involves converting raw, complex mineral resources into standardized, orderly concentrates that meet specifications for further processing in smelters or chemical plants [1]. The mined ore is sequentially subjected to primary crushing, vibrating screening, fine crushing, grinding, flotation and final thickening, as shown in Figure 1. Moisture content is a critical quality indicator for concentrated products, making thickening and dewatering a crucial step in the mineral processing workflow. The thickening process plays an essential role in achieving solid-liquid separation, with the thickener being the key piece of equipment in this operation [2].

In actual production, the operation of thickening and filtration relies heavily on assessing the operating conditions of the thickener, with the feed rate being a critical factor. The feed rate is a nonlinear, dynamic variable, and industrial operations often depend on manual experience, which can be subjective and imprecise. This makes it difficult for operators to accurately perceive the internal state of the thickener, leading to a relatively inefficient production process.

RuleML+RR'24: Companion Proceedings of the 8th International Joint Conference on Rules and Reasoning, September 16-22, 2024, Bucharest, Romania

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Issues such as low filtration efficiency and high energy consumption consequently arise. Therefore, optimizing thickener control requires accurate detection of the feed rate. In practice, ore feed rate detection typically relies on offline sampling or the installation of online analysis devices. However, due to the limitations of industrial environments, current detection methods fail to meet the requirements for real-time and accurate measurement [3].

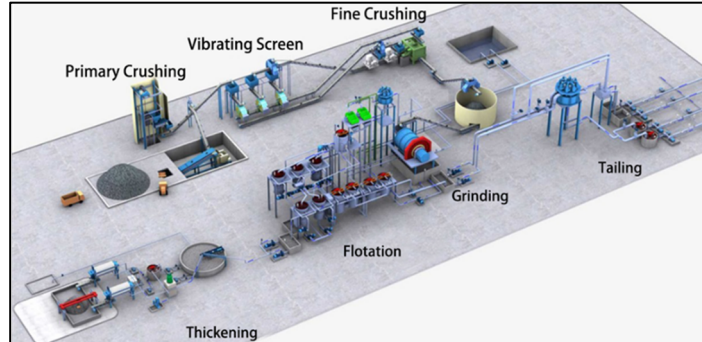


Figure 1. Schematic diagram of conventional beneficiation process and equipment.

With the development of soft sensing technology, data-driven regression models have been widely used to measure variables that are difficult to obtain directly in real-time. Moreover, recent years have seen breakthrough advancements in new intelligent sensing technologies, particularly in deep learning. Dynamic neural networks, represented by Recurrent Neural Networks (RNN), excel at capturing the temporal dynamics in sequential data. However, standard RNNs face issues like vanishing and exploding gradients when modeling long-time series, due to their indiscriminate memory of past data. To tackle this issue, Long Short-Term Memory (LSTM) networks were designed to selectively forget past information by incorporating gating units [4]. While LSTM offers superior performance, it comes with increased complexity and numerous parameters. The Gated Recurrent Unit (GRU) was thus introduced to simplify the LSTM structure while retaining its powerful performance [5].

In this study, the upstream processes of thickening are analyzed, and relevant data is used to implement intelligent perception of thickener feed rate using LSTM and GRU based models. The simulation results, along with actual data, verify that deep learning methods can effectively solve the problem of online detection of thickener feed rate.

2. Constructing and processing of datasets

The mineral processing workflow is a continuous process that includes crushing, grinding, flotation, and thickening/filtration, with each step closely interconnected. The output of one stage typically serves as the input for the next, forming a tightly integrated process chain. From prior knowledge, it is understood that the feed rate of the thickener is closely related to the grinding and flotation processes. Given the complexity of these processes which involve numerous pieces of equipment and sensors, this study selects 58 auxiliary variables from the grinding and flotation stages that have a strong correlation with the thickener feed rate.

The auxiliary variables' data can be detected in real-time at the industrial site and stored in a database. The raw data consists of actual operational data from the plant, with a sampling interval of 5 seconds, resulting in a total of 200,000 data sets. The selected time period for these samples effectively captures a wide range of conditions during normal process operation.

The raw data, directly sourced from on-site industrial detection equipment, inevitably contains missing values and random errors. Using such unprocessed data for model building can significantly reduce predictive accuracy. Therefore, data preprocessing is essential and involves the following steps:

(1) Handling missing values

Given the 5-second sampling interval, there are instances where equipment or sensor data change during sampling, leading to unsuccessful data capture. To address this, missing values in the raw data are identified and filled using forward filling, where the missing data point is replaced with the value from the preceding timestamp.

(2) Outlier detection

This study employs a moving median method to detect and eliminate outliers. Specifically, a moving window of length 70 is applied sequentially across the dataset. Within each window, any data point that deviates from the local median by more than five times the local standard deviation is classified as an outlier.

(3) Standardization and inverse standardization

The auxiliary variables exhibit significant differences in their values and distributions, rendering them unsuitable for direct input into the model. To mitigate the effects of differing dimensions among input variables, the data are standardized to have a mean of 0 and a standard deviation of 1. This standardized data serves as the input for model training. Consequently, the model's output, which is based on the standardized input, must undergo inverse standardization to revert to the original scale. The equations for standardization and inverse standardization are as follows:

$$X_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (1)$$

$$x_i = X_i(x_{max} - x_{min}) + x_{min} \quad (2)$$

where x_i : the i -th denormalized data, X_i : the normalized data, x_{min} and x_{max} : the minimum and maximum values of the sample set with N number of data, respectively.

(4) Evaluation criteria

The root mean square error ($RMSE$) is selected to evaluate the difference between the observed value y_i and the true value $pred_i$ of the model, and the calculated mean relative error (MRE) is selected to measure the overall deviation between the observed value and the true value to evaluate the quality of the model, as defined by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (y_i - pred_i)^2}{N}} \quad (3)$$

$$MRE = \frac{\sum_{i=1}^N |y_i - pred_i|}{N} \quad (4)$$

3. Intelligent perception models for thickener feed rate prediction

Intelligent perception models are developed for thickener feed rate evaluation using traditional deep learning-based LSTM-RNN and GRU-RNN. A subset of 10,000 data samples is selected from the dataset, and models are built using both this subset and the full dataset of 200,000 samples. The dataset contains 58 input variables, with the thickener feed rate as the output variable. The data is divided into training, validation, and test sets with a ratio of 0.7:0.15:0.15.

The simulation software Matlab® R2023b is used to build and run the models in a 64-bit Windows 11 stationary PC with an Intel(R) Core(TM) i9-12900H CPU and a 16.00 GB RAM.

3.1. Intelligent perception model based on LSTM-RNN

LSTM-RNN is a special recurrent neural network, composed of input gates, forget gates, and output gates which can process and memorize long-term series data. It can effectively alleviate the problems of gradient vanishing and gradient explosion in ordinary RNNs, and is suitable for solving the regression and prediction problems of long-term series. Figure 2 shows the process

of building the intelligent perception model based on LSTM. The hyperparameters are selected for random search optimization, and the Adam optimizer is used for training.

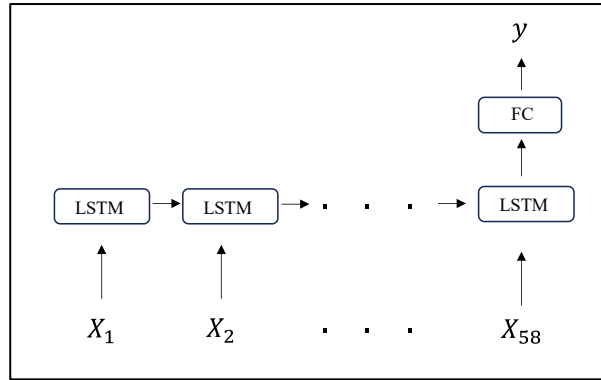


Figure 2. Structural diagram of the intelligent perception model based on LSTM.

The *RMSE* and the *MRE* for the predicted feed rate in ton/hour (*t/h*) using the test set containing 10,000 samples are 0.210 and 4.1%, respectively, and are 0.307 and 5.2% for the full dataset, respectively, as shown in Figure 3. However, the LSTM model's complexity, longer training time, higher hardware requirements, and increased number of parameters make the training process more challenging, which poses difficulties for its application in industrial settings. To address these issues, the use of a GRU network will be explored.

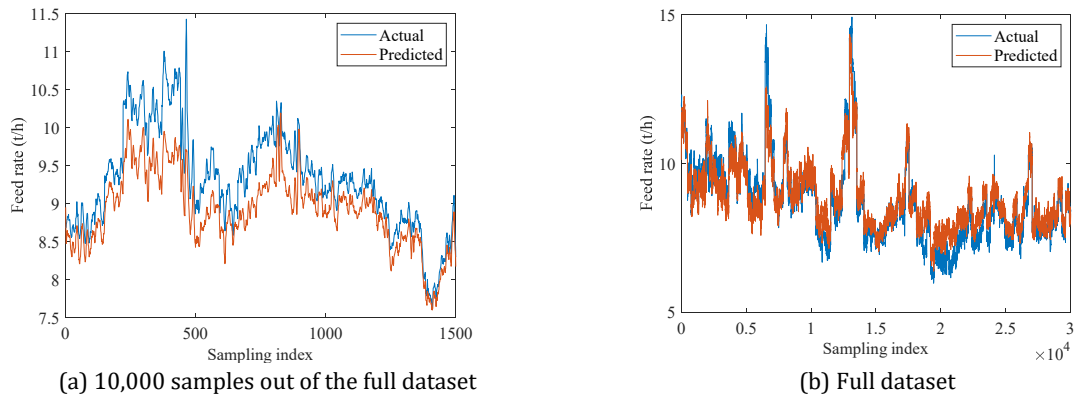


Figure 3. LSTM-RNN predicted feed rate output (*t/h*), compared with the actual values.

3.2. Intelligent perception model based on improved GRU

The GRU model is a further improved structural model of the LSTM, merging the input and forgetting gates of the LSTM and using only two gating units: the update gate and the reset gate. At the same time, the particle swarm (PSO) algorithm is used for hyperparameter optimization, which is an optimization algorithm based on swarm intelligence and finds the optimal solution through information sharing between individuals [6]. The structure of the GRU-based intelligent perception model is similar to that of the LSTM model in which the LSTM network is replaced by the GRU network, and the PSO algorithm is used to optimize the hyperparameters of the GRU.

As shown in Figure 4, the *RMSE* and the *MRE* for the predicted feed rate by PSO-GRU using the test set containing 10,000 samples are 0.153 and 3.5%, respectively, and are 0.136 and 3.4% for the full dataset, respectively. Actual result comparison shows that the performance of the PSO-GRU network can well meet the measurement accuracy requirements in the production line for the sample dataset of 10,000 sets, and the complete dataset with 200,000 sets. Additionally, the training time for the PSO-GRU model is 35min and 31s, shortened by 19% compared with of the LSTM model of 43min and 50s.

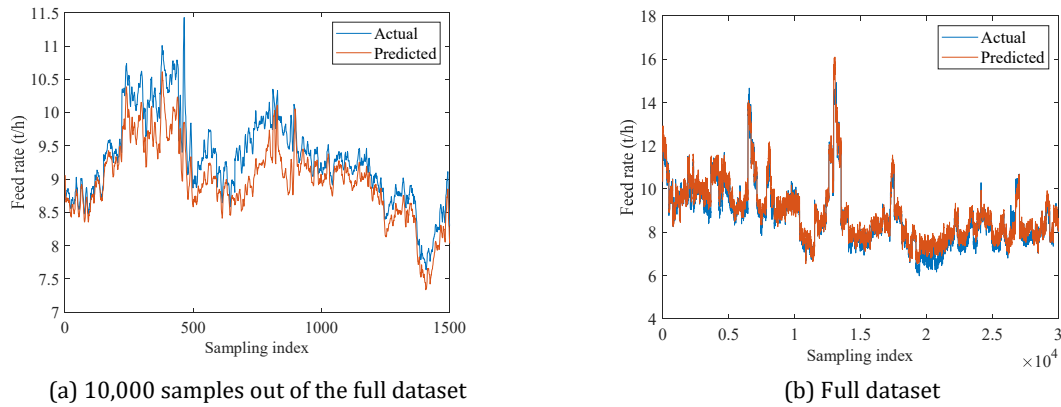


Figure 4. PSO-GRU predicted feed rate output (t/h), compared with the actual values.

4. Conclusions

The feed rate of the thickener is a crucial parameter in its operation. This study proposes several intelligent perception models to accurately predict the thickener feed rate, utilizing relevant variables from the grinding and flotation processes to address the challenge of online detection.

Two intelligent perception models are developed based on LSTM and GRU-RNN. The best performed GRU-RNN model and its advantages over LSTM network are analyzed. This deep learning-based approach could be applied to actual production, providing a foundation for the optimized control of the thickener.

Acknowledgements

This work was supported partially by the National Key R&D Program of China (Grant No. 2021YFC2902703), the Open Foundation of State Key Laboratory of Process Automation in Mining & Metallurgy/Beijing Key Laboratory of Process Automation in Mining & Metallurgy, China (Grant No. BGRIMM-KZSKL-2022-4, Grant No. BGRIMM-KZSKL-2023-10), Horizon Europe funded enRichMyData (Grant No. 101070284), and the bilateral project "BigDataMine" jointly funded by National Key R&D Program of China (Grant No. 2019YFE0105000) and the Research Council of Norway (Grant No. 309691).

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