Mathematical Modeling and Algorithm Application
ISSN: 3006-0842 | Vol. 2, No. 3, 2024

LSTM-based drive power matching and its economic analysis

Jiaqi Yao

Daqing Treasury Department, Daqing 163311, China

Abstract: The correlation coefficients of computerised well mining data and motor power, selecting indicators with high correlation as input data, predicting the minimum and maximum power of the unit based on LSTM neural network, and giving the template of drive system matching according to the theory of drive system matching technology formed for different models.

Keywords: Motor matching; Driving power; LSTM neural network, economic analysis.

1. Introduction

The input parameters of a predictive algorithm are the data features, attributes or variables that are used to train and execute the predictive model[1-2].These input parameters are used in predictive algorithms to construct models to make predictions or classifications by learning patterns and associations of data . Input parameters are usually represented as feature vectors of the model, with each feature corresponding to a data attribute. In the motor matching problem, the input parameters include data such as pump diameter, pump depth, stroke, strokes, daily liquid production, daily oil production, water content, dynamic liquid level, degree of submergence, pumping efficiency, oil pressure, casing pressure, lift height, power, system efficiency, and tonne of liquid power consumption[3-5].

2. Correlation function

Three commonly used correlation coefficients in data analysis are Pearson's correlation coefficient, Spearman's rank correlation coefficient and Kendall's correlation coefficient[6-7]. They are all used to measure the degree of association between two variables, but differ in their calculation methods and application scenarios. The choice of correlation coefficient depends on the nature of the data and the objective of the analysis. If the relationship is linear, the Pearson correlation coefficient can be used; if the relationship is monotonic but not necessarily linear, the Spearman or Kendall correlation coefficient can be used. Taking into account the characteristics of the data and the needs of the problem, selecting a suitable correlation coefficient can more accurately quantify the degree of association between variables.

3. Drive Matching Model

3.1. Network training

The LSTM neural network is similar to the traditional feed-forward network, as shown in Figure 1., in which the forward computation process is carried out in the direction of the black arrows, and the back propagation of error is carried out by the direction of the red arrows. The first step is to determine the network structure and loss function of the LSTM; secondly, initialise each parameter, then calculate an accuracy of the model through the loss function, and if it fails to achieve the accuracy we need, we need to carry out the update of the parameters; the updating criterion of the weights and bias terms should be such that they minimise the loss of the specified objective function in the training samples, i.e., to obtain the gradient when the parameter is derived through the loss function information, and then combined with the learning rate of the model and then update the parameters, the corresponding optimisation algorithm will generally be chosen to carry out the gradient update. When the gradient reaches the required accuracy, the parameters of the model can be determined, and the modelling of the LSTM model can be completed and applied to prediction or classification.

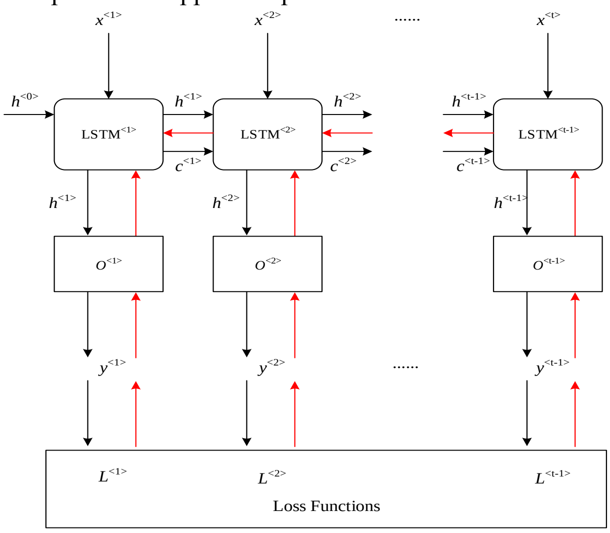

Figure 1. Diagram of the LSTM neural network training process

3.2. Optimisation of parameters

In the field of machine learning, for optimisation problems, the objective function is usually expressed as follows:

$$l(\theta) = E_{(x,y)\sim P_{(x)}} l(f(x,\theta), y) \qquad (1)$$

Where θ is the parameter to be optimised, x is the input value, f (x, θ) is the output value and y is the target output of the model. This expression reflects the loss function for a model with data (x, y). Whereas it is desired to find the parameter θ that minimises the loss function, i.e., to solve the following optimisation problem, the traditional gradient descent method calculates the objective function by computing the average loss over all the training data:

$$l(\theta)=\frac{1}{N}\sum_{i=1}^{N} l(f(x_i,\theta),y_i) \tag{2}$$

$$\nabla l(\theta)=\frac{1}{N}\sum_{i=1}^{N} \nabla l(f(x_i,\theta),y_i) \tag{3}$$

where N denotes the number of training samples, while the parameters are updated with the formula:

$$\theta_t=\theta_{t-1}-\alpha\nabla l(\theta_{t-1}) \tag{4}$$

Obviously, when there is a lot of training data, i.e., N is very large, the computational volume will be very large, and the computational efficiency of the model will be reduced and the computational time will be increased. In order to improve the computational efficiency and accuracy of the prediction results, there are corresponding optimisation methods for the training of parameters in the training of neural networks, and two commonly used parameter optimisation methods are introduced below.

4. Data screening and grouping

4.1. Capacity efficiency screening

Hundred-metre-tonne liquid power consumption is an important evaluation index of electric power consumption in the oilfield extraction process, which has an important role and significance in industrial production and energy management, and also provides a powerful data guide for the comprehensive analysis of the whole oil extraction system. By monitoring and analysing the power consumption of 100m tonnes of fluid, enterprises can identify the links with high power consumption and take measures to improve the efficiency of power use, which helps to reduce production costs and improve enterprise competitiveness. By reducing the power consumption of 100m tonnes of fluid, companies can reduce their negative impact on the environment, reduce their carbon footprint and achieve sustainable production.

The 100m tonnes of fluid power consumption for all the individual wells in the block is shown in Figure 4.1, with most of the individual wells having a 100m tonnes of fluid power consumption of 5kWh/(t-100) or less.

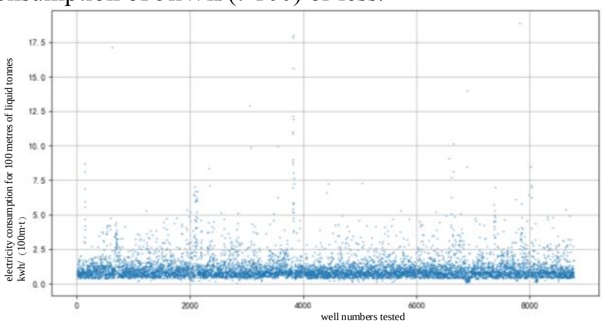

Figure 2. Electricity consumption per 100 metres of fluid in a single well

Zooming in on Figure 2., as shown in Figure 3, the power consumption of 100 metres of tonnes of fluid is concentrated between 0.4kWh/(t-100) and 2kWh/(t-100) for most single wells.

Larger 100 m tonnes of liquid power consumption indicates that the well is less efficient and should not be used as an input to the neural network for learning, so data from power-consuming individual wells with 100 m tonnes of liquid power consumption greater than 1 kWh/(t-100) were discarded.

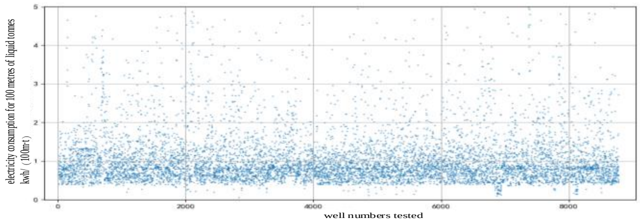

Figure 3. Amplification of electricity consumption for 100 metres of tonnes of fluid in a single well

4.2. Grouping of types

(1) Types of energy-saving pumping units

In the oil and gas industry, different types of energy saving technologies are usually used in order to increase the efficiency of the pumping units and to reduce the energy consumption.

Most of the pumping units in this block are offset pumping units, and the number of well sets of other types (conventional and large reduction ratios) is low, so only motor matching data for offset pumping units is retained.

(2) Motor type

When it comes to different types of energy-saving motors, each of which has its own unique energy-saving principles and operating characteristics, the matching relationship is different, and should be grouped together for power generation.

Using 1, 2, 3, 4, 5, 6, and 7 to represent high start single speed, high start two speed, high turndown single speed, high turndown two speed, normal Y series, normal Y series two speed, and permanent magnet respectively. They are filtered so that only one motor type data is fed into the neural network for each training session

(3) Oil pumping machines

The predictions should be trained in groups for different pumping parameters, and Figure 4 shows the programme code when the pumping parameter 10-3-37 pumping is retained.

```
dataframe = dataframe[dataframe['f1'] == 10]
dataframe = dataframe[dataframe['f2'] == 3]
dataframe = dataframe[dataframe['f3'] == 37]
```

Figure 4. Screening procedure for pumping parameters

4.3. Eigenvalue Generation

According to the correlation calculation results, the input parameters of the neural network are selected: pump diameter (mm), daily liquid production (t), stroke*stroke, dynamic liquid level (m), degree of submergence (m), suspension point load, rated torque, low and high speed; and the output of the neural network is low and high power.

5. Driving system matching simulation

(1) High-start single speed

100 wells are selected as the test set, and the remaining individual wells are used as the training set, and the power matching prediction results for the high start single-speed motors are shown in Fig. 5, which is able to obtain the basic laws.

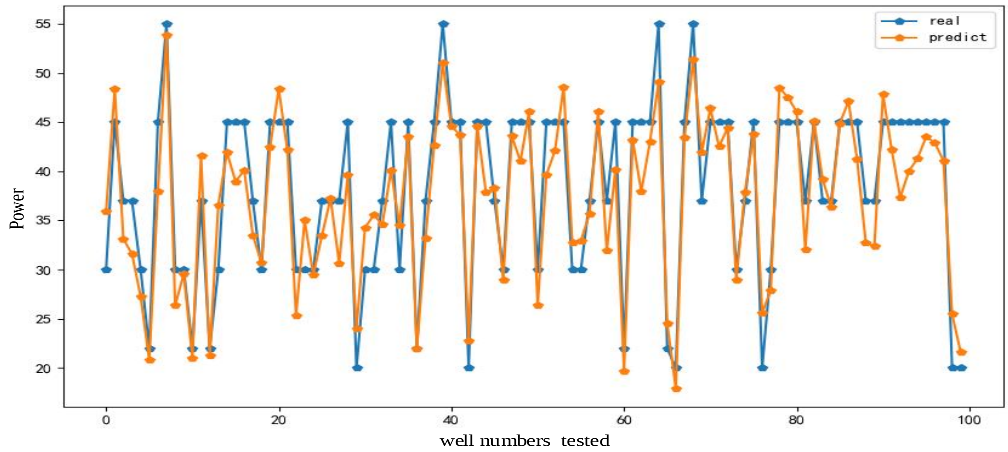

Figure 5. Power matching prediction results for high start single speed motor

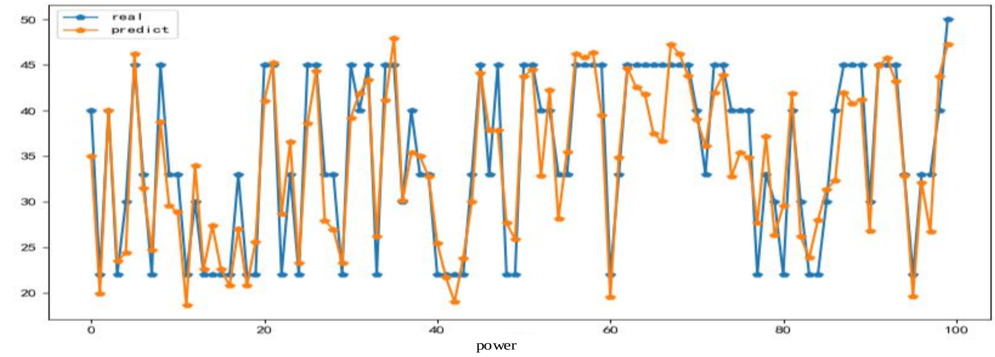

Figure 6. Predicted results of low power matching for high start two-speed motors

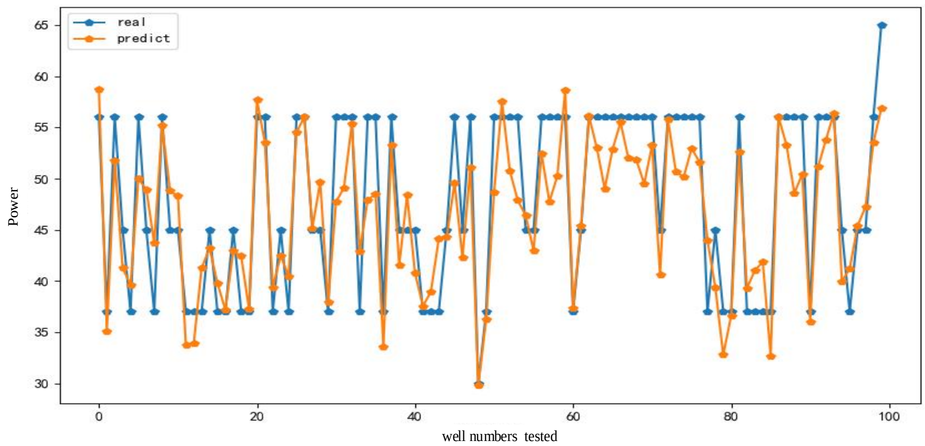

Figure 7. Predicted results of high power matching for high start two-speed motors

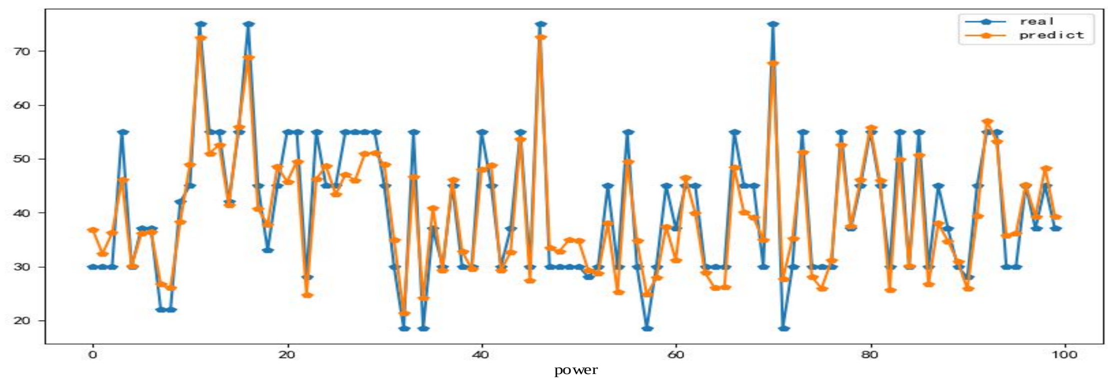

Figure 8. Predicted results of power matching for high-turn single-speed motors

(2) High-start double speed

100 wells were selected as the test set and each of the remaining single wells were used as the training set, and the low power matching prediction results for the high start two-speed motors are shown in Fig. 6, which is able to obtain the basic laws.

100 wells were selected as the test set and each of the remaining single wells were used as the training set, and the

predicted results of the high power matching of the high start two-speed motors are shown in Fig.7, which is able to obtain the basic laws.

(3) High-turn single speed

100 wells are selected as the test set and the remaining individual wells are used as the training set, the power matching prediction results for the high-rotation single-speed motors are shown in Fig. 8, and the basic laws can be obtained.

6. Summary

Build a single-well power matching model based on LSTM neural network, select Pearson correlation coefficient as the analysis method of correlation coefficient of each parameter, apply the use of artificial intelligence algorithm classification and identification, form the theory of matching technology of drive system for different models, take the parameters of daily liquid production grading and lifting height grading as the preferred parameters of the matching scheme of single-well hardware equipment, and form the template for matching of hardware equipment in accordance with the principle of the optimal energy consumption, which has good applicability.

References

[1] Baker Hughes Oilfield Operations LLC; Patent Application Titled "Biased Centralizing Arms Bearing In Submersible Pump Motor" Published Online (USPTO 20200067378)[J]. Politics & Government Week, 2020.

[2] Sergio G Lopez, Sebastian Samwald, Sally Jones, Christine Faulkner. On the pixel selection criterion for the calculation of the Pearson's correlation coefficient in fluorescence microscopy. [J]. Journal of microscopy, 2024.

[3] Huimin Han, Jilin Guo. Design and Implementation of Marine Vessel Photovoltaic Power Generation System Based on Automatic Power Matching Technology [J]. Journal of Coastal Research, 2019, 94 (sp1):Chunyou Zhang, Liang Wang, Hong Li. Experiments and Simulation on a Late-Model Wind-Motor Hybrid Pumping Unit[J]. Energies, 2020, 13 (4).

[4] Shu-you Zhang, Ye Gu, Xiao-jian Liu, Jian-rong Tan. A knowledge push technology based on applicable probability matching and multidimensional context driving [J]. Frontiers of Information Technology & Electronic Engineering, 2018, 19 (2).

[5] A A Belsky, V S Dobush, V A Morenov, M S Sandyga. The use of a wind-driven power unit for supplying the heating cable assembly of an oil well, complicated by the formation of asphalt-resin-paraffin deposits[J]. Journal of Physics: Conference Series, 2018, 1111 (1): 012052-012052.

[6] Lan Song, Stobart Richard, Wang Xiaonan. Matching and optimization for a thermoelectric generator applied in an extended-range electric vehicle for waste heat recovery [J]. Applied Energy, 2022, 313

[7] Qian Wang, Dawei Meng. A study of the matching of impellers and motors for contra-rotating fan based on electromagnetic-fluid coupling analysis [J]. Advances in Mechanical Engineering, 2016, 8 (11).