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Research on Torque Prediction Method of Drill String Based on TCN-KAN

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Abstract

To accurately predict drill string torque, enhance drilling efficiency, and reduce operational costs, this paper addresses the issues of limited generalization capability and high complexity in torque prediction models during horizontal well drilling by conducting research on intelligent prediction methods based on deep learning. An intelligent torque prediction model based on TCN-KAN is proposed. Multi-source characteristic variables such as drilling depth, rotary speed, and weight on bit are selected for model training, and a TCN comparative model is established for experimental validation. The results show that the TCN-KAN model outperforms the comparative model in evaluation metrics such as root mean square error and mean absolute error, achieving a prediction accuracy of 98.58%. It effectively captures the complex nonlinear relationships between torque and drilling parameters. This model is suitable for drilling torque monitoring, intelligent feed optimization, and drilling decision support, providing reliable technical support for the automation and intelligence of drilling operations.

Keywords

Drill string torque prediction; Kolmogorov-Arnold network; Intelligent drilling optimization Component

1. Introduction

With drilling operations increasingly advancing into deeper and complex formations, the complexity of operations and safety requirements continue to rise, making the demand for related technologies more urgent. Therefore, achieving accurate prediction of drill string torque has become a critical research direction for enhancing drilling safety and efficiency.

The prediction methods for drill string torque have undergone distinct stages of development: From the 1940s to the 1970s, methods relied primarily on engineer experience, empirical formulas, and statistical models, which generally suffered from limited accuracy and insufficient applicability. From the late 1970s to the early

1990s, methods based on physical models gradually emerged, significantly improving prediction accuracy and reliability by establishing mathematical models for factors such as formation, drilling tools, and drilling fluids. Since the 21st century, with the rapid development of deep learning and artificial intelligence technologies, these have been successfully applied in various drilling fields, such as cuttings identification, borehole stability evaluation, and downhole fault diagnosis [1]. However, systematic research on drill string torque prediction remains relatively limited.

Studies indicate that factors such as well depth, drilling fluid density, weight on bit, pump pressure, and well inclination are key variables influencing torque [2]. Compared to the limitations of traditional methods in handling high-dimensional features and complex constraints, deep learning demonstrates significant advantages, enabling efficient modeling at a lower cost under existing resource conditions and providing more scientific solutions to engineering challenges. Therefore, by thoroughly analyzing the aforementioned key parameters and constructing suitable deep learning models, it is possible to achieve higher accuracy in drill string torque prediction. This, in turn, can help reduce equipment wear, improve drilling efficiency, ensure operational safety, and maintain borehole integrity [3].

The author selected fields such as well depth, well inclination, drilling fluid density, weight on bit, pump pressure, and drilling fluid density from wells in the same block as features and conducted a series of experiments with drill string torque as the label. A TCN-KAN model was proposed by combining the TCN model with KAN and applied to drill string torque prediction.

2. Model Introduction

2.1. Kolmogorov-Arnold network

Multilayer Perceptron (MLP) is a widely used fully connected feedforward neural network, commonly applied to tasks such as classification and regression. Each neuron in an MLP is connected to all neurons in adjacent layers, enabling it to effectively model complex relationships within data. However, this also introduces a large number of parameters. When dealing with high-dimensional data, excessive parameters not only significantly increase computational burden and reduce training efficiency but are also prone to optimization challenges such as gradient vanishing or explosion, thereby limiting further improvements in model performance. Therefore, in practical applications, optimization strategies or structural improvements are often required to mitigate such issues.

In contrast, the theoretical foundation of KAN stems from the Kolmogorov–Arnold representation theorem, which states that any multivariate continuous function can be expressed as a combination of several univariate continuous functions and addition operations. The core structural innovation of KAN lies in replacing the linear weights in traditional MLPs with learnable activation functions. A schematic diagram of its shallow structure is shown in **Figure 1**.

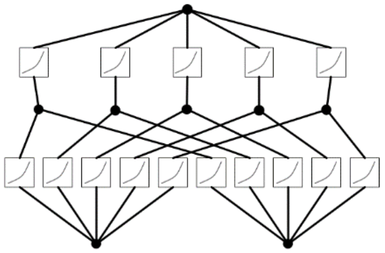

Figure 1. Diagram of a shallow KAN structure

2.2. Temporal Convolutional Network

Temporal Convolutional Network (TCN) is a temporal modeling architecture based on one-dimensional convolutional neural networks. By integrating causal convolution, dilated convolution, and residual connections, it can map inputs of arbitrary lengths to outputs of equal length while effectively capturing long-term dependencies. The causal convolution mechanism ensures that each output step is influenced only by current and historical inputs, avoiding interference from future information and preserving temporal causality. To expand the receptive field, the model incorporates dilated convolution, as illustrated in **Figure 2**. Through exponentially increasing dilation factors, the input is sampled at intervals, allowing the receptive field to expand exponentially with the number of layers. This design enables the model to cover long historical sequences with fewer layers, efficiently capturing long-term temporal patterns while mitigating issues such as parameter redundancy and gradient problems commonly encountered in deep networks.

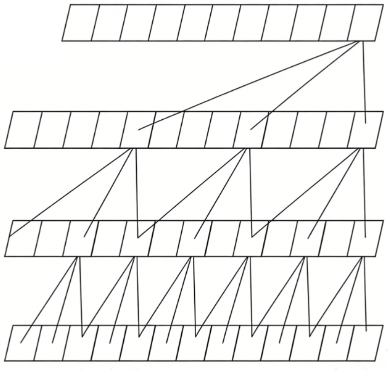

Figure 2. Dilated Convolution Structure

3. Establishment and Implementation of the TCN-KAN Model

3.1. Model Architecture

A drill string torque prediction model based on TCN-KAN is proposed, in which the fully connected layers at the end are replaced with a KAN architecture, thereby constructing a novel TCN-KAN drill string torque prediction model. Compared to the traditional MLP structure, KAN is capable of handling deeper nonlinear problems with fewer parameters and offers stronger interpretability. The initial parameter settings of the model are shown in **Table 1**.

Table 1. Model parameters

Model name	Model parameters		
	Batch Size	Kernel Size	Dilation Factors Sequence
TCN	128	3	[1,2,4,8]
TCN-KAN	128	3	[1,2,4,8]

3.2. Network Training and Result Analysis

This study utilizes drilling operation data from a specific block provided by a drilling company, which includes parameters such as drilling depth, pressure, rotational speed, rate of penetration, and hook load. To enhance data quality, preprocessing was first performed: key features were selected, outliers were removed, missing values were handled, and the data were standardized to eliminate the influence of varying units. Consequently, drilling depth, pressure, rotational speed, rate of penetration, hook load, and other relevant parameters were selected as input variables for the model [4]. The dataset was split into training and test sets in an 8:2 ratio and underwent normalization to improve the model's generalization capability.

In this study, the Mean Squared Error (MSE) was used as the loss function, and the TCN-KAN model was trained for 100 iterations using the Adam optimizer. Through multiple experiments and result analyses of various models, their predictive performance was comprehensively evaluated to identify the optimal intelligent prediction model. **Figure 3 and Figures 4** shows the prediction results of each model on the test set, where the blue curve represents the actual measured values and the red curve represents the predicted values of the corresponding model.

From **Table 2**, it can be clearly observed that the prediction curve of the TCN model still deviates from the actual measured data, with a Mean Absolute Error (MAE) of 1.04331 and a Mean Squared Error (MSE) of 1.83386. The TCN model exhibits relatively low prediction accuracy, significant fluctuations, and moderate fitting performance. In contrast, the TCN-KAN hybrid model, improved with the KAN architecture, shows enhancements in both prediction accuracy and curve fitting. The MAE decreases to 0.8474, and the MSE decreases to 0.91394. Compared to the TCN model, the TCN-KAN model achieves an 18.78% reduction in MAE and a 50.16% reduction in MSE.

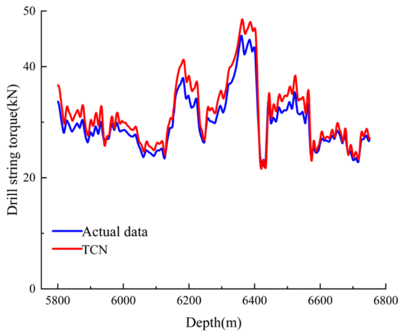

Figure 3. Prediction of TCN

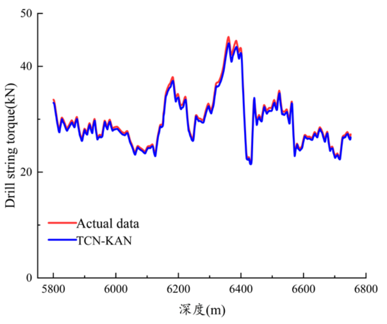

Figure 4. Prediction of TCN-KAN

Table 2. Comparison of prediction errors of different forecasting methods

Model name	Model parameters		
	MAE	MSE	R2
TCN	1.04331	1.83386	0.92209
TCN-KAN	0.84746	0.91394	0.98589

4. Conclusion

This paper analyzes the intrinsic relationships between multiple key drilling parameters—such as rotary table speed, rate of penetration, hook load, and drilling fluid inflow/outflow rates—and torque, and proposes an intelligent drill string torque prediction model based on TCN-KAN. The model utilizes TCN to capture long-term dependencies in drilling time-series data, and replaces the fully connected layers with a KAN structure, leveraging nonlinear spline functions to achieve more accurate function approximation, thereby significantly improving the overall performance and generalization capability of the model. Comparative experiments with the TCN model validate the superiority of the TCN-KAN model in terms of prediction accuracy, generalization ability, and computational efficiency.

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