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EGU26 GENERAL ASSEMBLY

A DNN–LSTM–GPC framework for TOC prediction in marine shales of the X Block using multi-source logging data

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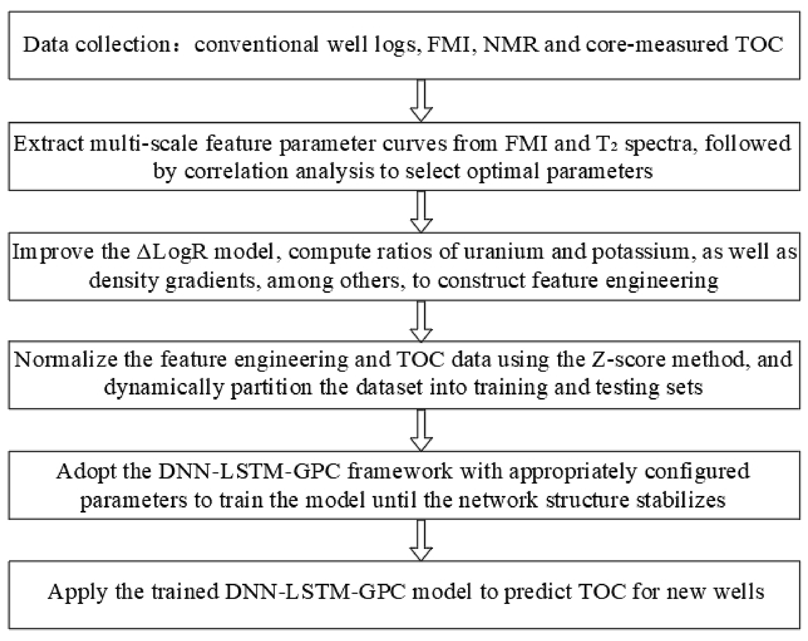
Abstract

Marine shales of X-block are featured with poor organic matter, over maturity and complex mineralogical assemblages, which collectively result in weak organic-related logging responses. As a consequence, conventional total organic carbon (TOC) evaluation methods exhibit substantial uncertainties associated with baseline calibration and parameter generalization, thereby limiting prediction accuracy and robustness.

To overcome these limitations, this study develops a physics-constrained deep learning framework for TOC prediction that integrates multi-source logging data using a hybrid DNN – LSTM – GPC architecture. In addition, an improved ΔLogR model and region-specific rock-physics constraints are embedded within the deep learning framework to ensure physical consistency and geological interpretability.



Workflow of TOC Prediction Using the DNN-LSTM-GPC Framework

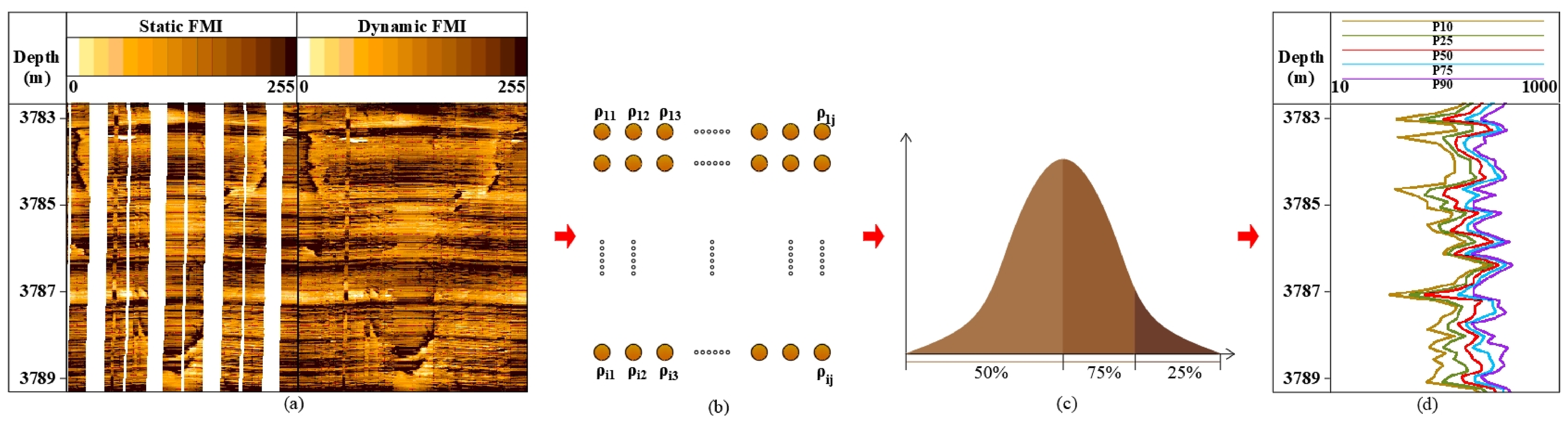
Methods

FMI characteristic curve

To address the issue of blank stripes in electrical imaging logging caused by insufficient electrode coverage, this paper introduces a conditional generative adversarial network (CGAN) for restoration. On this basis, quantile statistical sorting is applied along the depth direction to rank the micro-resistivity values within each depth interval, from which characteristic percentiles (P_{10}~P_{90}) are sequentially extracted and concatenated into a continuous characteristic curve. This curve quantitatively characterizes the statistical distribution of micro-resistivity values and their vertical heterogeneity.

$$N = \rho_{(1,1)} \le \rho_{(1,2)} \le \rho_{(1,3)} \dots \le \rho_{(i,j)} \qquad k = k_0 + d \qquad (0 \le d \le 1)$$

$$k = (j-1)\frac{p}{100} + 1 \qquad P_p = \rho_{(i,k_0)} + d \times (\rho_{(i,k_0+1)} - \rho_{(i,k_0)})$$



Schematic Diagram of CGAN-Based Blank Band Filling and Micro-Resistivity Characteristic Curve Extraction

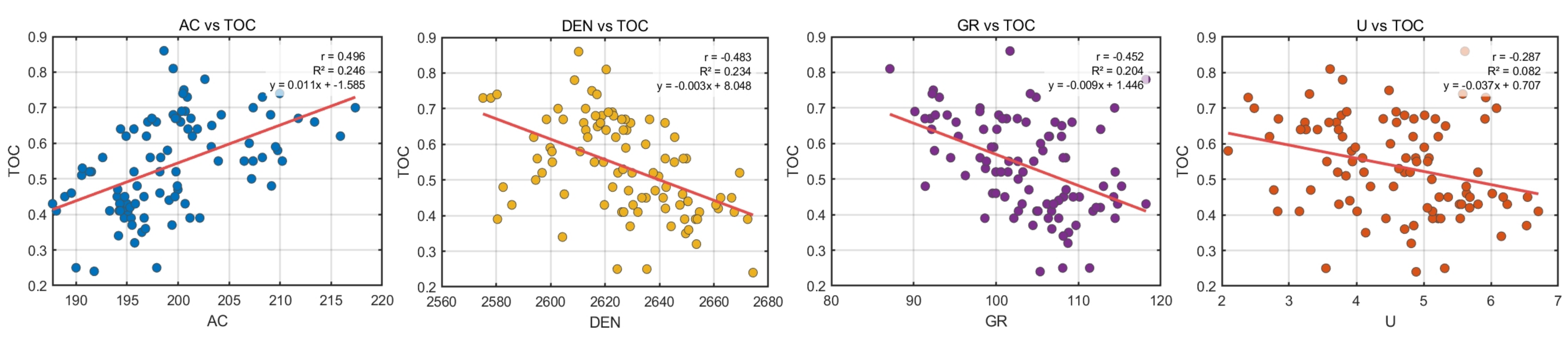
NMR characteristic curve

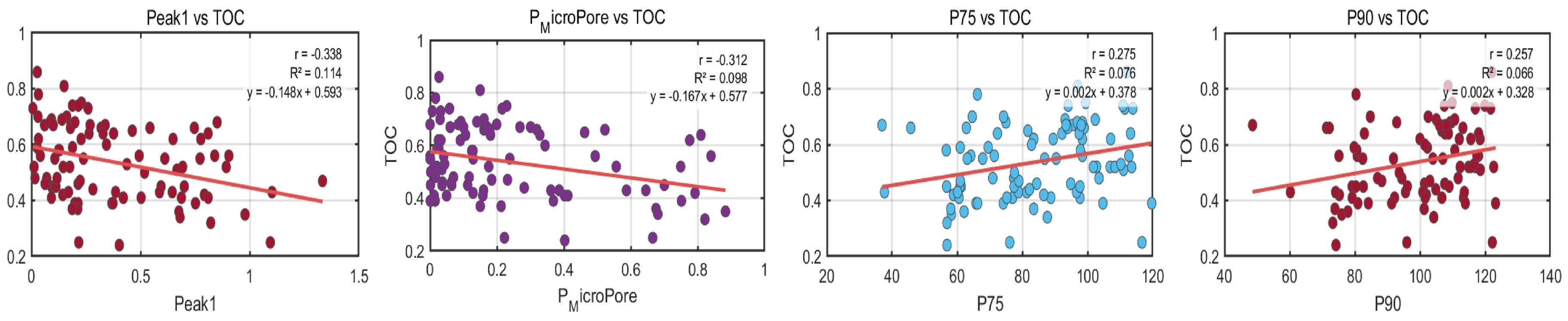
The nuclear magnetic resonance T_2 spectrum contains a wealth of pore structure information. In this paper, four key parameters are extracted: the T_2 geometric mean (T_{2GM}), which reflects the average pore radius; the kurtosis, which characterizes the concentration or dispersion of pore size distribution; the micropore ratio ($P_{MicroPore}$), which quantifies the relative contribution of nanoscale pores to total porosity; and the peak area ratio (PeakRatio), which distinguishes the relative proportions of organic and inorganic pores. These four parameters characterize pore structure features and organic matter occurrence states from different dimensions, complement each other.

$$T_{2GM} = \exp\left(\frac{\sum_{i=1}^{n} A_i \cdot \ln(T_{2i})}{\sum_{i=1}^{n} A_i}\right) \quad Kurtosis = \frac{\sum_{i=1}^{n} A_i \cdot (T_{2i} - \mu)^4}{\sigma^4} - 3 \quad P_{MicroPore} = \frac{\int_{T_2<2ms} A(T_2)dT_2}{\int_{all} A(T_2)dT_2} \quad PeakRatio = \frac{\int_{Lp}^{Rp} A(T_2)dT_2}{\int_{all} A(T_2)dT_2} * 100\%$$

Correlation analysis

The Pearson correlation coefficient is employed to analyze the associations between various well logs and core TOC.





Feature engineering

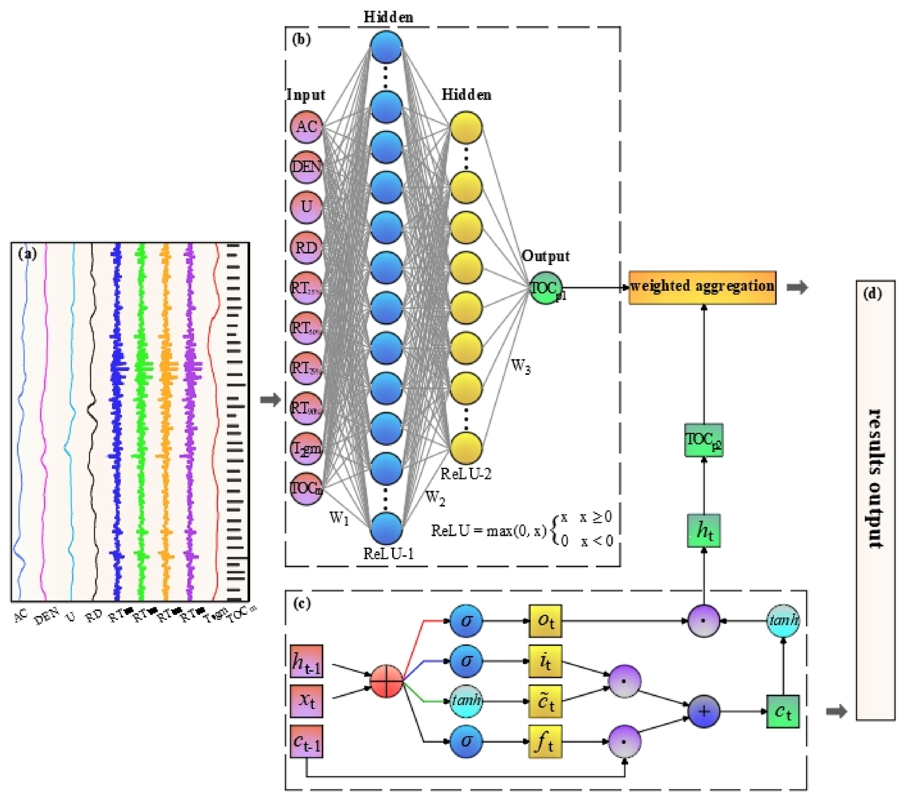
Well logs with an absolute correlation coefficient greater than 0.25 with respect to core TOC are selected as input features, thereby constructing a multidimensional feature matrix that integrates information on organic matter distribution, pore structure, and lithological variations. This strategy provides input parameters with high signal-to-noise ratio and physical relevance for TOC prediction.

$$P_{75baseline} = \frac{1}{|W_t|}\sum_{i\in W_t} P_{75i} \qquad P_{90baseline} = \frac{1}{|W_t|}\sum_{i\in W_t} P_{90i} \qquad AC_{baseline} = \frac{1}{|W_t|}\sum_{i\in W_t} AC_i$$

$$\Delta \log R = \log(P_{75}/P_{75baseline}) + \log(P_{90}/P_{90baseline}) + 0.02 * (AC - AC_{baseline})$$

$$\Rightarrow F = \left[\Delta \log R; GR; \frac{U}{K}; \nabla_Z DEN; Peak1; Peak2; Peak3; P_{MicroPore}\right]$$

DNN-LSTM-GPC



Structure diagram of the DNN-LSTM-GPC framework

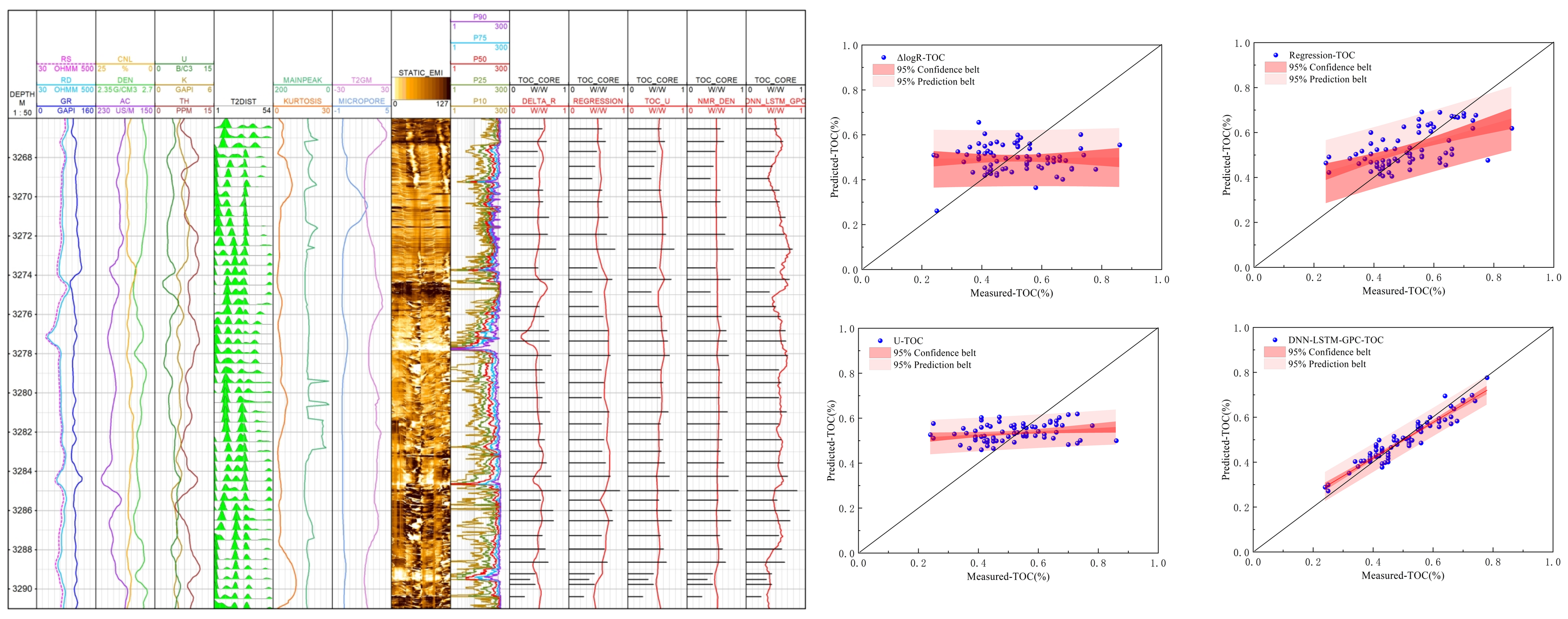
The proposed approach integrates the capacity of deep neural networks (DNNs) to extract laterally local and complex features with the advantage of long short-term memory (LSTM) networks in sequential modeling along the depth direction, while incorporating regional geological constraints as prior information to ensure the geological plausibility of the prediction results[1,2].

$$TOC_Y = \begin{cases} TOC_{DNN}(d) & , S > d \\ 0.2 \cdot TOC_{DNN}(d) + 0.8 \cdot TOC_{LSTM}(d) & , S \le d \end{cases}$$

$$TOC_Y = \max(0, \min(2, TOC_Y))$$

Results

Application results demonstrate that the proposed method achieves superior prediction performance in low–organic-matter marine shales, yielding a root mean square error of 0.08% and a coefficient of determination (R^2) of 0.90. The model consistently outperforms ΔlogR methods，multivariate regression, uranium curve method, while maintaining stable predictive capability in intervals exhibiting pronounced TOC heterogeneity.



Comparison of TOC prediction results for Well A from multiple models

Conclusions

The integration of physics-constrained deep learning with multi-source logging data provides a reliable and effective approach for TOC evaluation and favorable reservoir identification in low–organic-matter marine shale systems.

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References： 1.Wang, J. & Cao, J. A Lithology Identification Approach Using Well Logs Data and Convolutional Long Short-Term Memory Networks. IEEE Geosci. Remote Sensing Lett. 20, 1–5 (2023);

2. Wang, H., Wu, W., Chen, T.,et al. An improved neural network for TOC, S1 and S2 estimation based on conventional well logs. J. Pet. Sci. Eng. 176, 664–678 (2019).