DNN Enabled Real-Time Modeling of EM LWD Tool Responses in Complex Subsurface Formations

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***Abstract*—In this paper, a fast forward modeling framework for predicting the logging-while-drilling (LWD) tool responses is presented. Unlike the traditional numerical methods based on the finite difference or finite element method, the proposed approach makes use of a deep neural network (DNN). During the offline training stage, the DNN is trained to extract the mapping from the formation parameters to tool responses. Then it can be used to predict the tool responses immediately given the formation parameters. The target application is the directional LWD operations, where the formation resistivity model has to be updated on the fly. This requires an extremely efficient forward modeling of LWD tool responses. Numerical tests are presented and results indicate the proposed method is outperforming the conventional methods.**

I. Introduction

Electromagnetic (EM) logging-while-drilling (LWD) is widely used in directional drilling for oil and gas exploration [1]. During the drilling process, the well trajectory is adjusted on the fly. This requires updating the formation resistivity model in real time to facilitate decision-making of the well trajectory. Equivalently, the inverse problem must be solved in real time, where the forward modeling is executed in an iterative manner. Therefore, an extremely efficient forward modeling of LWD tool responses is indispensable. In current literature [2], [3], [4], [5], [6], the majority of research works performs the forward modeling by assuming the formation is 1-D parallel layered, i.e., the formation property remains constant within each horizontal layer and all layers are stacked vertically. However, this assumption does not hold for complex formations, such as fault and pinch-out. The 1-D forward modeling will consequently give rise to incorrect results for such complex formations.

Recently, Yan *et al.* [7] investigated a 2-D pixel-based inversion that employs the 2.5-D finite difference method (FDM) as the forward modeling for complex formations. The inversion results indicate the 2-D inversion can infer both formation resistivity and dielectric constant with high accuracy. However, the computational cost of the 2-D inversion is inevitably high due to the time-consuming forward modeling. The objective of this paper is to develop a surrogate model to accelerate the 2.5-D forward modeling. The surrogate model is constructed by a deep neural network (DNN). To estimate the accuracy of the DNN, tool responses predicted by the DNN are compared against the exact values obtained by the 2.5-D FDM calculation [8]. The comparison gives a good match with a relative error less than 5%. The obtained acceleration of 24000 indicates the DNN is capable of performing fast forward modeling of EM LWD tool responses in complex formations.

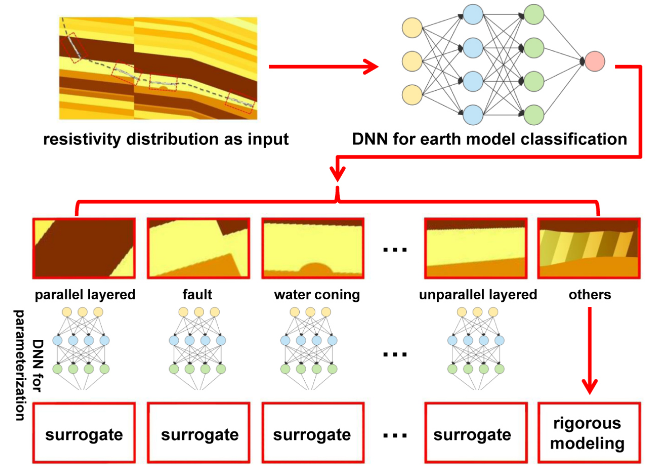

Fig. 1. Diagram of the DNN-assisted fast forward modeling.

II. DNN Assisted Fast Forward Modeling

The diagram of the DNN assisted forward modeling is shown in Fig. 1. In the first stage, a DNN is used for earth model classification. Briefly, the formation resistivity distribution is fed into a neural network and the output is the formation type. Several particular formation types are considered here. As long as the formation type is determined, the corresponding surrogate model maps the formation parameters such as resistivity and geological structures to the tool responses. For each formation type, a fast surrogate model will be generated using another DNN. The design of the DNN contains two stages, including offline training and online prediction, as shown in Fig. 2(a). During the training stage, we use synthetic data generated by the 2.5-D FDM algorithm to feed into the DNN. The DNN is able to extract the mapping from the formation parameters to tool responses until the training converges, i.e., $\mathcal{Y} = \mathcal{F}(\mathcal{M})$ in Fig. 2(a). Then the DNN is used to immediately predict the tool responses for given formation parameters.

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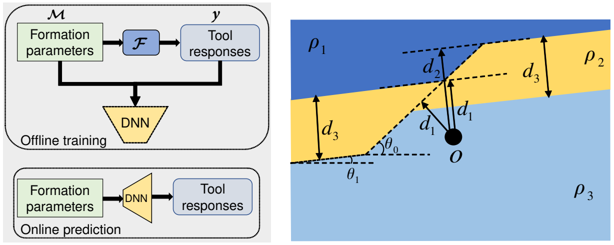
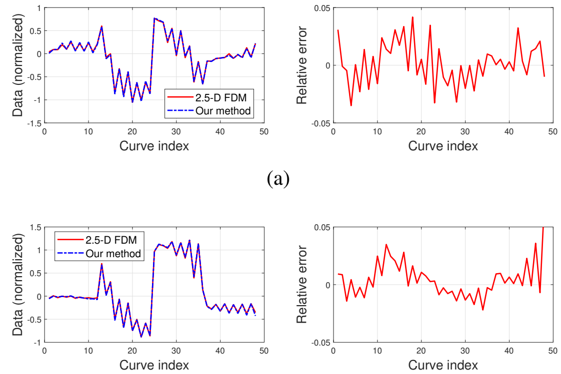


(a) (b)

Fig. 2. (a) Diagram of the DNN training and predication; (b) 2-D fault formation.



(a)

(b)

Fig. 3. Predicted tool responses of fault formation: (a) Example 1; (b) Example 2.

III. Numerical Results

In this section, simulation results are presented to demonstrate the efficiency and accuracy of the proposed DNN as a forward modeling tool. For an illustrative purpose, we only show a particular formation type, fault, as depicted in Fig. 2(b). It should be noted that the construction of the surrogate model can be extended to other complex formations, such as water coning. In Fig. 2(b), the fault structure is characterized by 9 independent parameters, including distances (d_0, d_1, d_2, d_3), tool's angles (θ_0, θ_1), and resistivities (ρ_1, ρ_2, ρ_3). The range and number of sampling points of the parameters are listed in Table I. There will be 405000 sets of the parameters in total. Note that 2 spacings between the receiver and transmitter and 3 operating frequencies are used. In addition, for each spacing and frequency, there are 8 tool responses [7]. Therefore, 48 tool responses will be generated for each group of formation parameters. The synthetic dataset will be a 405000×48 table. 90% of the synthetic data is used for training and the remaining data is used for test. Two examples are shown in Fig. 3. In each example, 48 tool responses are computed by both 2.5-D FDM and the surrogate model given the formation parameters. Left subplots in Fig. 3 show good agreements between the two approaches. The right subplots indicate that maximum relative errors are less than 5%. Meanwhile, in an Intel Core i9 $2.9\,\text{GHz}$ CPU laptop, the conventional FDM takes about $120\,\text{s}$ to calculate 48 tool responses for each group of formation parameters, while the DNN only takes $0.005\,\text{s}$. This suggests that the DNN has the capability of accelerating the forward modeling up to 24000 times for a single group of formation parameters.

TABLE I
Formation model parameters and their range.

Parameter	Min. Value	Max. Value	Sampling points
d_0	$-15\,\text{m}$	$15\,\text{m}$	6
d_1	$-10\,\text{m}$	$10\,\text{m}$	5
d_2	$-10\,\text{m}$	$10\,\text{m}$	5
d_3	$3\,\text{m}$	$20\,\text{m}$	3
θ_0	$65°$	$115°$	3
θ_1	$-10°$	$10°$	3
ρ_1	$1\,\Omega\,\text{m}$	$100\,\Omega\,\text{m}$	4
ρ_2	$1\,\Omega\,\text{m}$	$100\,\Omega\,\text{m}$	5
ρ_3	$1\,\Omega\,\text{m}$	$100\,\Omega\,\text{m}$	5

IV. Conclusion

A fast and accurate methodology to simulate the LWD tool responses in complex formations is presented. In principle, the proposed method makes use of a deep neural network to build the surrogate models for different formation types. Numerical examples suggest that the proposed method enables real-time forward and inverse modeling of electromagnetic LWD in complex formations.

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