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Case Study: Using AI&ML to Generate Well Logs in Santa-Fe Field, Kansas

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Abstract

Well logs are one of the most crucial field measurements in formation evaluation and reservoir characterization. They have been utilized for almost a century since 1926 when Schlumberger brothers invented the electric logs. During the past decades, well logging tools and interpretation techniques have gone under many advancements and developments adding to its value as a critical field measurement. However, there are several thousand cases in which due to issues such as technical problems of the tools, operational state of the well, age of the well, time sensitivity, and economical reasons few or many of the logs are not measured. In addition to missing logs, there are many cases that well logs are measured but have a bad quality and are not reliable. Nowadays, Artificial Intelligence and Machine Learning (AI&ML) techniques can be used to provide the missing data and/or identify the bad quality ones.

In this case study which is used on "Santa Fe" field data located in Kansas, a sequence of nine Artificial Neural Networks (ANNs) were trained, calibrated, verified, and tested through blind validations to generate synthetic well logs step-by-step only based on GR (Gamma Ray) and caliper logs. This study consists of ten wells where nine of them were used for training, calibration, verification, and one well has been used for the blind validation of the ANNs performance. The blind validation well is a well that was never used in any of ANNs training, calibration, and validation and is assumed not to exist. The order of the nine ANNs sequence is to predict Neutron Porosity, Sonic Travel Time, Density, Photoelectric, and Array Resistivities (R10, R20, R30, R60, R90), respectively. The order of ANNs sequence is determined based on logs' "Key Performance Index (KPI)", a technique based on the Fuzzy Set Theory (Mohaghegh, 2017). In all nine ANNs prediction of the blind validation well, only GR and Caliper measurements are used, and any other logs that are used as an input are generated synthetically by the previous ANNs. The results successfully show that all missed logs for multiple wells can be generated with high accuracy based on minimum available logs like GR and Caliper.

Introduction

For almost a century, well logs have been a crucial part of oil and gas exploration and reservoir characterization. Once a well is drilled, whether to be completed or plugged and abandoned, it is essential to run well logs to make such decisions. Wells logs provide the most economical key information about the subsurface formation through instruments lowered into the well. Since the 1930s, several logging tools like Gamma Ray, Resistivity, Sonic, and Nuclear have been developed and improved continuously. Each of these logging tools provide some critical information as a piece of puzzle about the rock and the fluid down the well when all pieces are put together, a correct decision and interpretation can be made.

Ideally, petrophysicists would like to have all the logs available for a well. However, due to missing data in old wells, feasibility, tool failure, bad data or economic reasons, it is mostly a doomed wish. Artificial Intelligence and Machine Learning (AI&ML) is a popular technique used to generate missing data due to the complex nature of the well logs. There are several studies in literature that show generation of missing logs using AI&ML using different techniques like Artificial Neural Networks (ANN), Recurrent Neural Networks, and ensemble algorithms like Random Forest, Gradient Boosting and Decision Trees (Akinnikawe et al. 2018, Alimohammadi et al. 2020, Alzate et al. 2014, Zhang et al. 2018).

Usually, it is a common practice to run as many logs in an exploration well to collect as much as possible information from the new field (Bateman, 2012). However, by drilling more wells and developing the field by time, the number of measured logs shrink, and in many cases, it is only sufficed to running the basic log like Gamma Ray (GR) after some point due to economic reasons. What separates this study from previous ones is addressing this issue. The objective of this study was generating a full set of Neutron, Density, Sonic, Photoelectric, and Array Resistivity logs for a well only based on basic logs of GR, and Caliper. To achieve this goal, available logs from 10 wells in Santa Fe field located in Haskell County, Kansas was collected. After data processing, series of ANNs were successfully trained, calibrated, verified, and finally blind validated.

Artificial Intelligence and Machine Learning (AI&ML)

According to IBM, Artificial Intelligence (AI) is the technology that mimics the problem-solving and decision-making capabilities of the human brain. Microsoft defines Machine Learning (ML), a subset of AI, as the process of helping a computer to identify and learn patterns within the data without direct instruction by using mathematical algorithms to make model and predictions. With more data and experience, the results of machine learning become more accurate like human learning process through practice.

In traditional engineering, all the physics-based models are performed through mathematical equations. The fact is that such mathematical equations mostly include assumptions, interpretations, and simplifications. There are mathematical equations that may also include preconceived notions, and biases about certain physical phenomena. During the AI-based modeling of physical phenomena when the data is a combination of actual field measurements and data that is generated through mathematical equations like Hybrid Models, and Physics-Informed Neural Network, based on AI-Ethics (Mohaghegh 2021), it becomes clear that the developed AI-model is not based on reality of AI rather it includes assumptions, interpretations, simplifications, preconceived notions, and biases.

In this study, authors do not intend to explain the architecture or mathematics of neural networks as they can be found in depth in several articles. However, it is intended to show a workflow that honors the original definitions of AI&ML and follows AI-Ethics by not including assumptions, interpretations, simplifications, preconceived notions, and biases.

Data Preparation and Partitioning

Publicly available well logs data of 10 wells from Santa Fe field covering an area of 2×2 miles were acquired. For all these 10 wells, logs of Gamma Ray (GR), Neutron Porosity (NPHI), Bulk Density (RHOB), Sonic Travel Time (DT), Photoelectric Factor (PE), and Array Resistivities (RT10, RT20, RT30, RT60, and RT90) were available from 4,100 ft to 5,500 ft. This data was used as the database. Figure-1 shows the distribution of the wells in the study area.

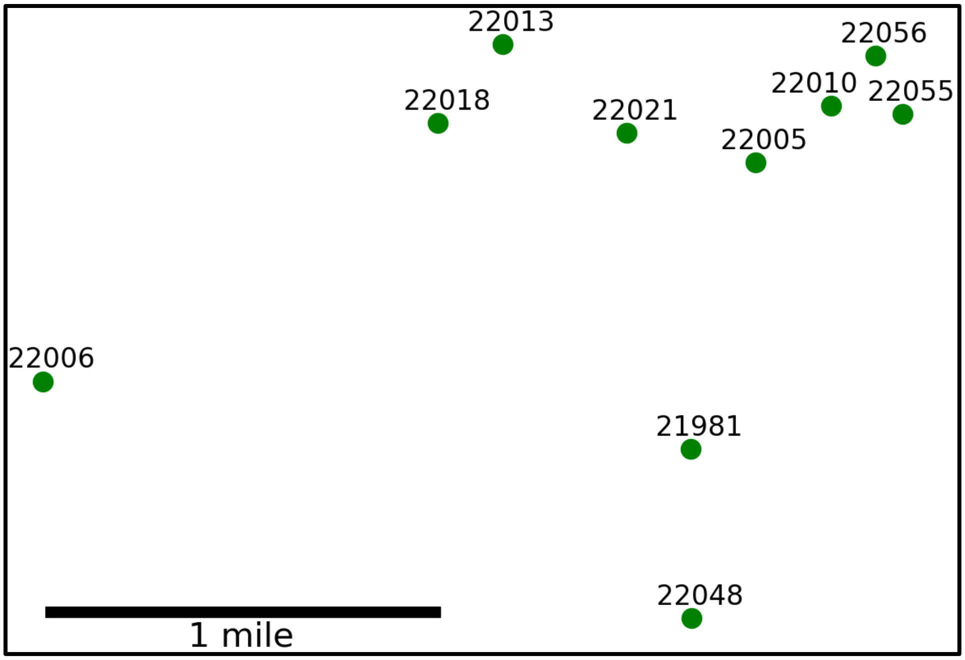

Figure-1: Well locations in Santa Fe field

After normalizing the data in the database, a common practice in ANN models for faster training, the data was partitioned into two major datasets: First the training dataset with three subsets of training, calibration, verification; And second the blind validation dataset.

Training dataset is the data used for training, calibration, and verification of the ANN. This dataset includes the data from nine wells. Training dataset is randomly portioned in three categories with 80%, 10%, 10% allocation for training, calibration, and verification respectively. Training data is used as input for the ANN. Calibration data is used to avoid overfitting (memorization of the ANN), and verification data is used to evaluate the performance (bias) of the ANN model. Blind validation dataset consists of the data from the well 22055 that was not used in any part of training, calibration, and verification (Figure-2). In other words, it was assumed that the data from blind validation well did not exist at the time of training. The reason why well 22055 was chosen as blind validation is because all measurements of this well falls in the range of minimum and maximum measurements in the database.

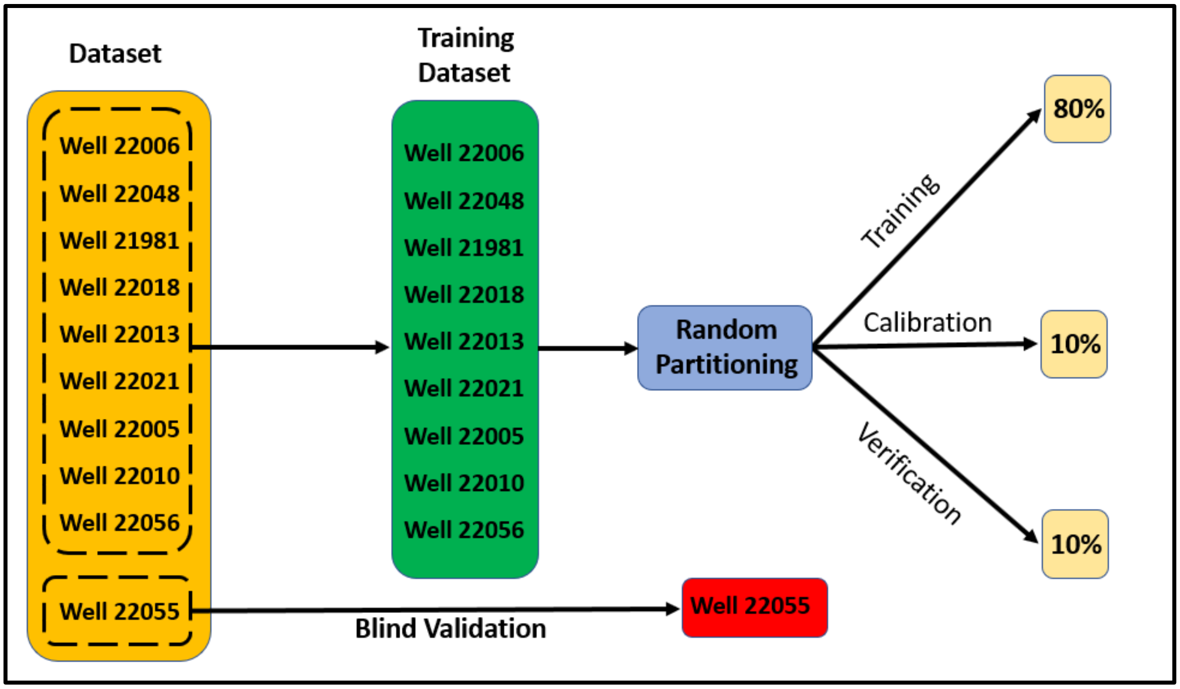

Figure-2: Data Partitioning

Modeling

Implementing the idea of generating logs based on only available logs of GR and Caliper, a series of sequential ANNs should be generated in the order that output of each ANN will be used as an input of the next ANN sequence. For that, nine ANNs are required to model NPHI, RHOB, DT, PE, RT10, RT20, RT30, RT60, and RT90. However, the order of ANN sequence plays an important role in both performance of the models and the training time. To find the correct order of ANN sequence, Key Performance Indicator, "KPI", a technique based on Fuzzy Pattern Recognition (Mohaghegh et al. 2013), was used to identify the relative order of input importance in the dataset (Figure-3).

The challenging part of the modeling was the first ANN sequence, NPHI, due to the low number of input logs (only GR and Caliper). To generate new features, Supervised Fuzzy Clustering technique was implemented on the GR log to generate three classes (clusters) based on the GR value. Figure-4 shows the implementation of Fuzzy Clustering on GR.

Having the order of ANNs sequence and generating input features, a workflow was then prepared for all nine ANNs. Figure-5 illustrates the workflow of ANNs sequence.

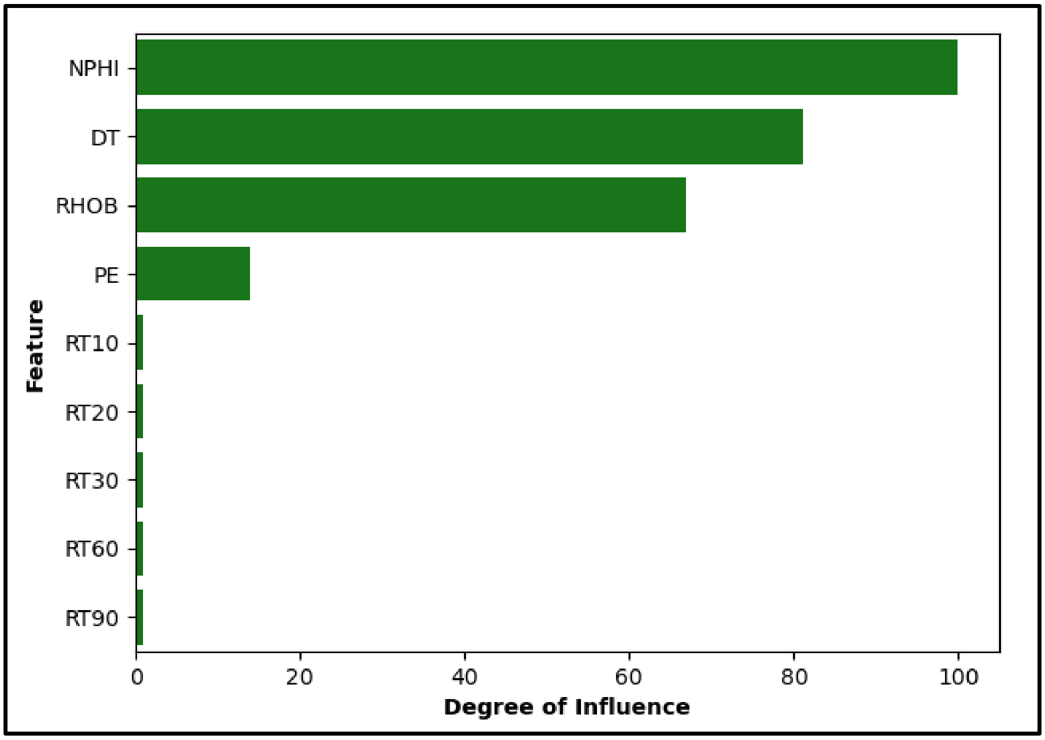

Figure-3: Degree of influence of logs based on Fuzzy Set Theory

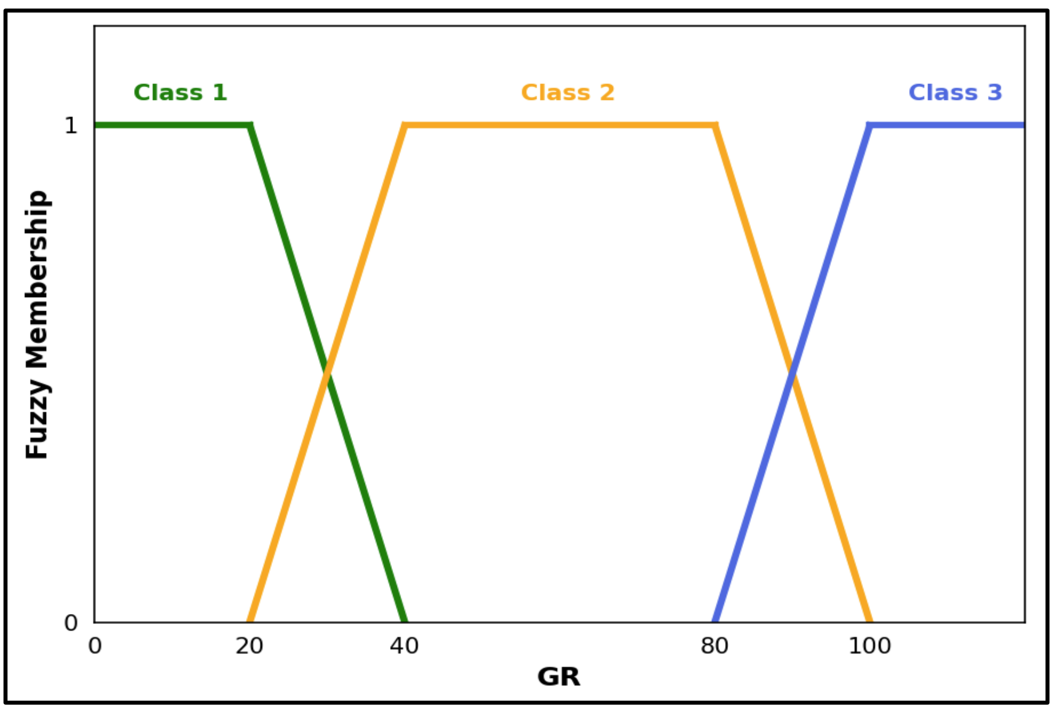

Figure-4: Fuzzy Clustering used for feature generation

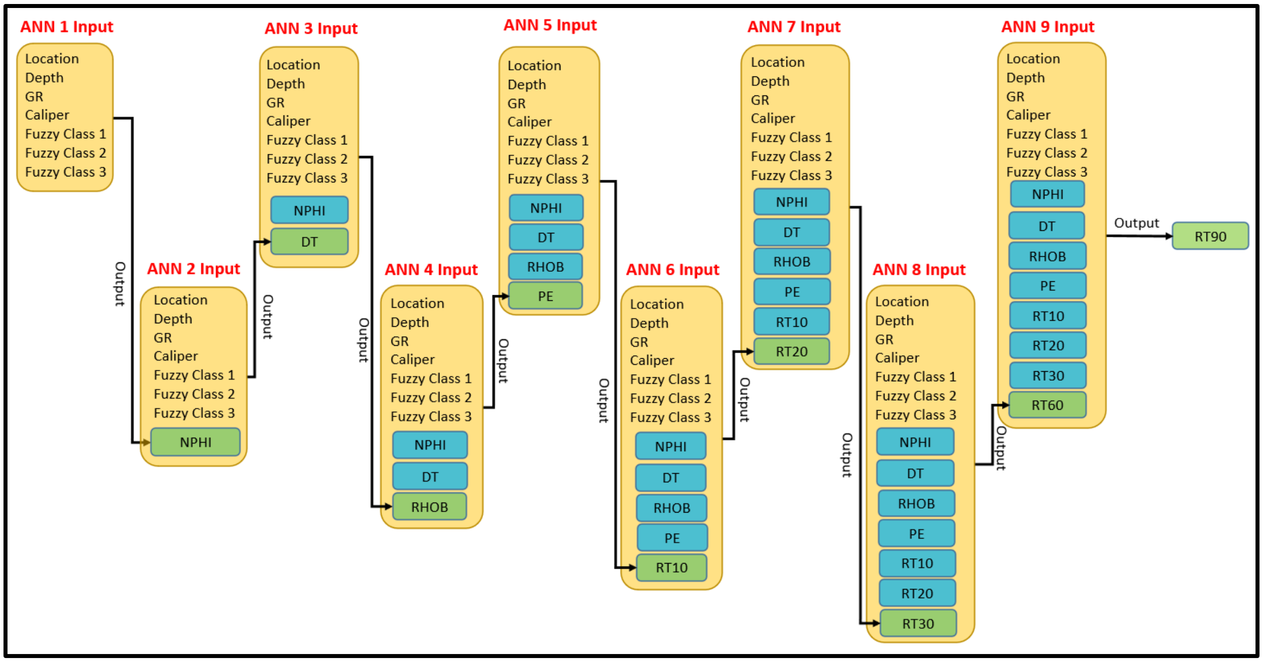

Figure-5: Workflow of ANNs sequence with inputs (features) used in each model

Final part of modeling was allocated to optimizing the architecture and hyperparameters of the ANNs. As the authors strongly believe the performance of models is mostly related to the data and the features generated and used during training, the hyperparameter tuning was done only on the first ANN and same hyperparameters were used for all other nine ANNs. The good performance of the results confirms this. More details of ANN structure and hyperparameters are shown in Table 1.

Table 1: ANN architecture and hyperparameters used in training

ANN Architecture	Multi-Layer Perceptron
NO. of Hidden Layers	4
NO. of Neurons in each Layer	128, 128, 64, 32
Optimizer	ADAM
Learning Rate	Adaptive
Activation Function	ReLU

After modeling was completed, the predictions of each ANN model was compared to the real measurements of both training and blind validation wells. To quantify the comparison between predictions and measurements, metrics of R^2, MSE (mean squared error), RMSE (root mean squared error), and MAE (mean absolute error) were calculated.

Results

First ANN model was trained to predict the Neutron Porosity (NPHI). Since it was the first sequence of ANN, and consequently had the least number of logs available (only GR and Caliper), it was expected to have the lowest accuracy ($R^2 = 83\%$) among all ANNs models. Figures A-1 and A-2 illustrate the comparison results of ANN model with actual data for training dataset and blind validation. To have a better visualization and resolution on results of blind validation, well 22055, the completely modeled interval is divided to three sections and for each section; predictions and actual data are compared together in Figure-6. As a petrophysical point of view, the results in Figure-6 are acceptable even though the model has some difficulties when NPHI spikes to very high or low values. This issue was addressed and resolved later.

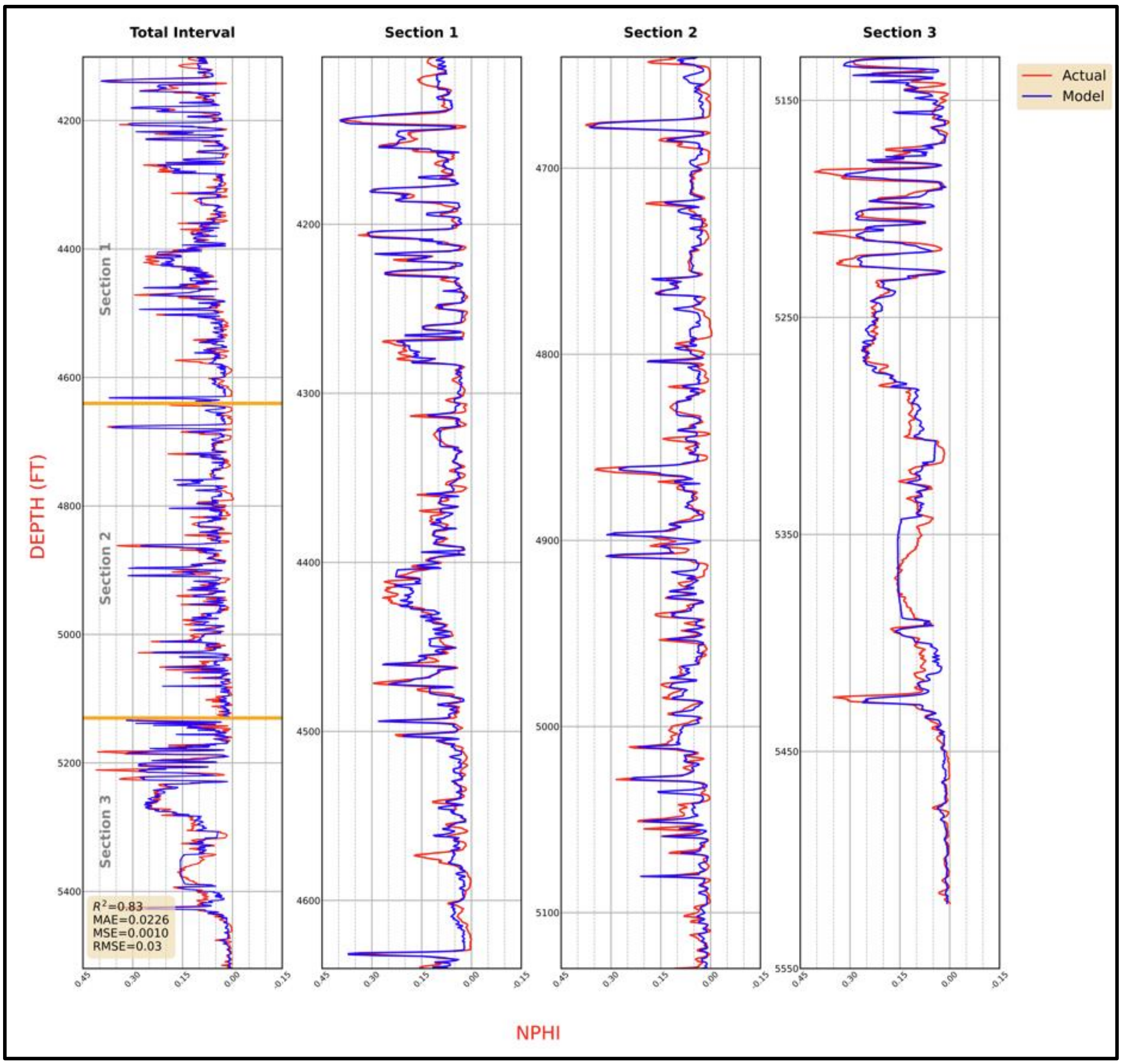

Figure-6: Blind validation, well 22055, NPHI results compared with actual measurements

Results of ANN1, NPHI model, were used as input for ANN2 to predict Sonic Travel Time, DT. It was expected that ANN2 perform better than ANN1 as it was trained with more features. Figure-7 compares the results of DT with measurements, on contrary shows slightly lower performance (R^2=81%) respect to NPHI (R^2=83%). The reason of lower performance could be contributed to the sonic tool measuring higher travel time due to the Cycle Skipping effect and/or presence of shales. On Figure-7, these effects on the performance of the ANN2 model can be corroborated in several depths where DT records high values above 90 µsec/ft and wash-out was detected. This issue was addressed later. Figures A-3 and A-4 illustrate the comparison results of ANN model with actual data for training dataset and blind validation in more details.

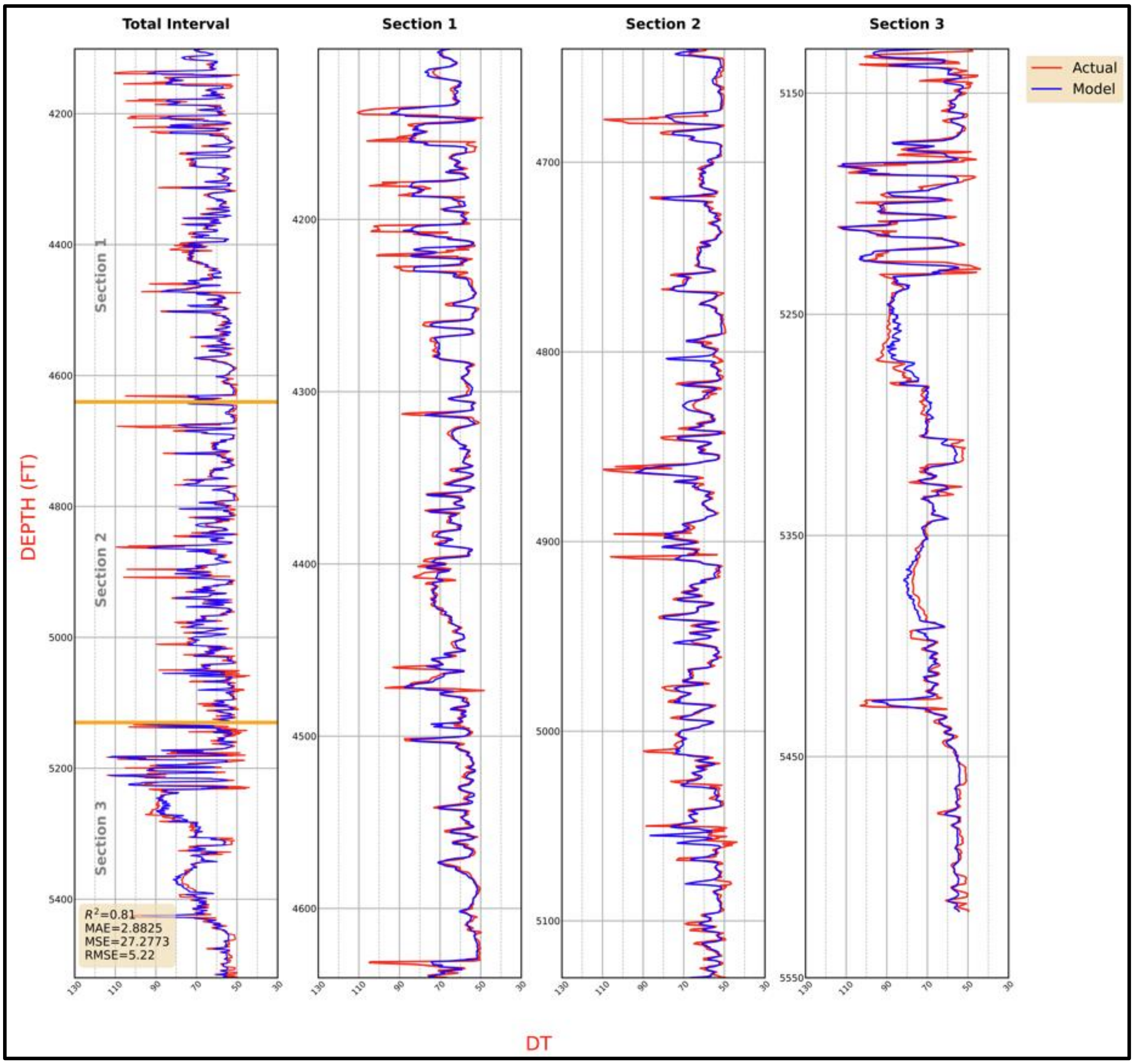

Figure-7: Blind validation, well 22055, DT results compared with actual measurements

Sequentially, results of ANN1 (NPHI) and ANN2 (DT) were used as new inputs for ANN3 to predict the RHOB. As the number of features (inputs) increases, it was expected that the neural network receive more information and train better. RHOB blind validation results are shown in Figure-8. More details can be found in figures A-5 and A-6.

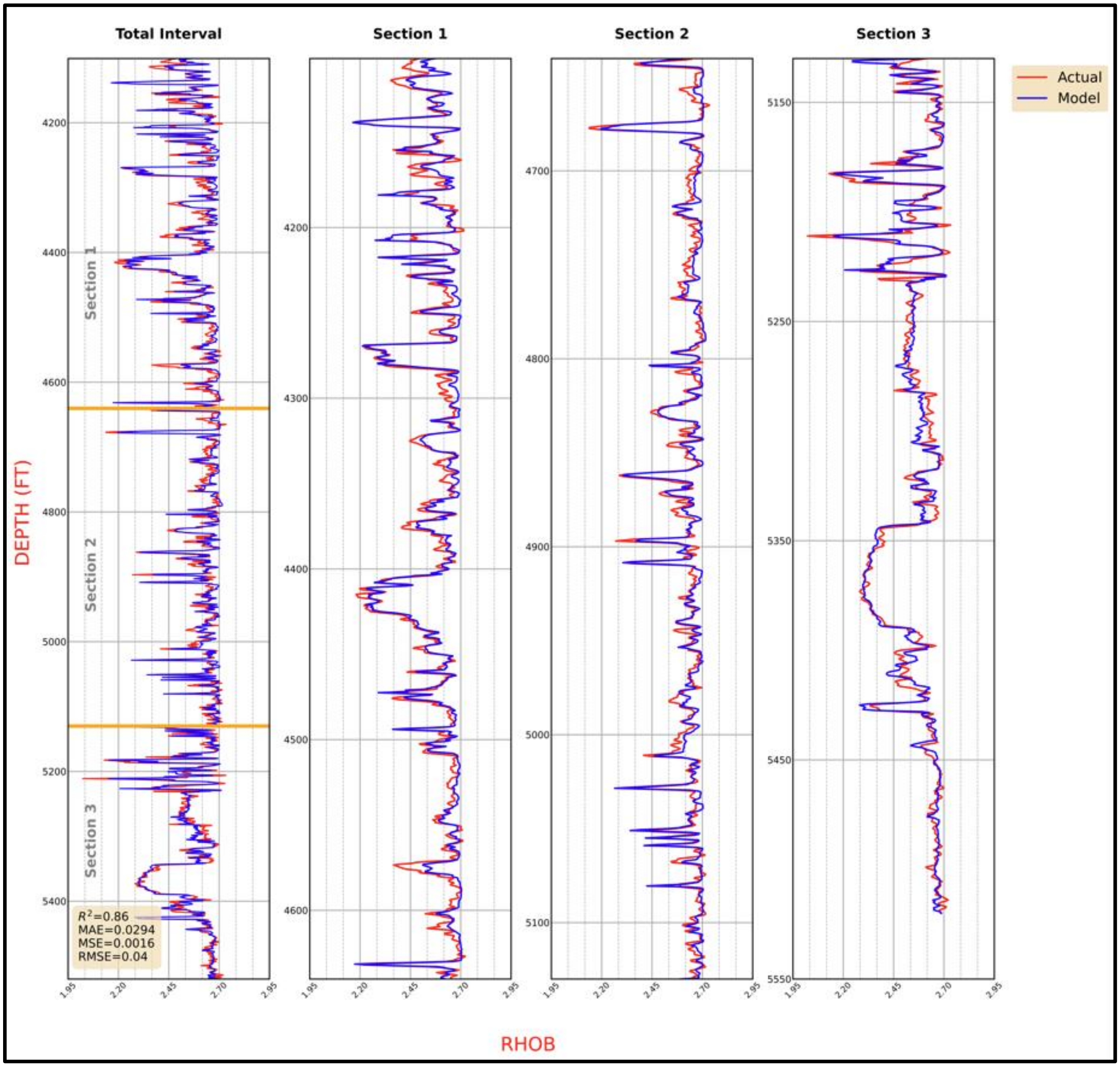

Figure-8: Blind validation, well 22055, RHOB results compared with actual measurements

Next neural network to be trained was ANN4 to predict photoelectric effect, PE. For that, previous neural networks' outputs, NPHI, DT, and RHOB, were used as new features. Results of the PE modeling suggests that the model has learned the pattern of PE behavior very well with minimal issues when actual PE is measured to be around 5 barns/electron. The comparison results of modeling and actual measurements are presented in Figures 9, A-6, and A-7.

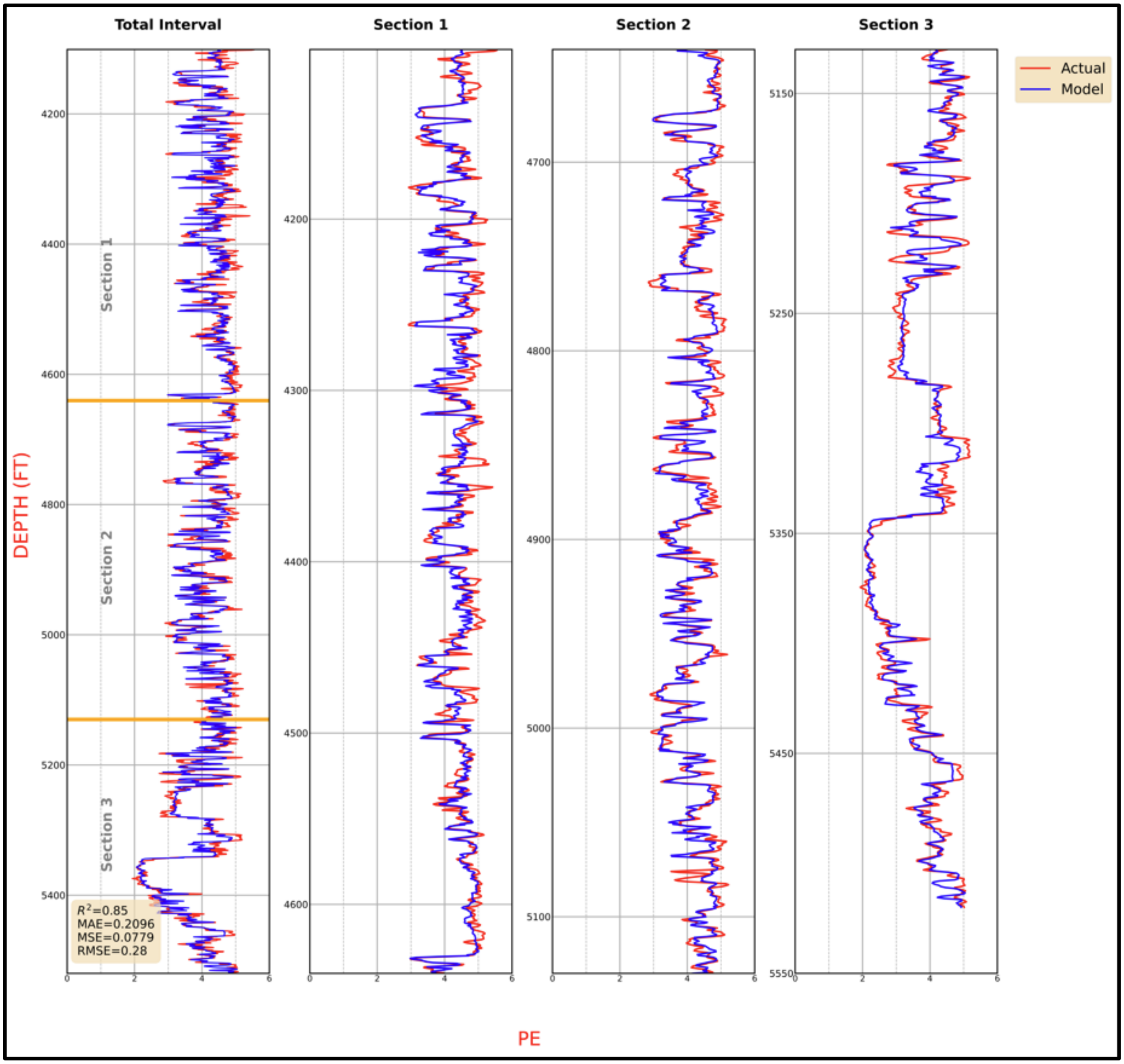

Figure-9: Blind validation, well 22055, PE results compared with actual measurements

Last logs to be trained and modeled were resistivity logs. Since the tool used for resistivity measurements was Array Induction Tool, five resistivity measurements with depths of investigation of 10, 20, 30, 60, and 90 inches were used and trained sequentially in ANN5 through ANN9. From ANN6 which models RT20 through ANN9 modeling RT90, trainings and modeling have achieved 100% accuracy. Figures 10 through 14 shows the results of blind validation resistivities RT10, RT20, RT30, RT60, and RT90 respectively. More details about performance of training, calibration, and verification are provided in figures A-9 through A-18.

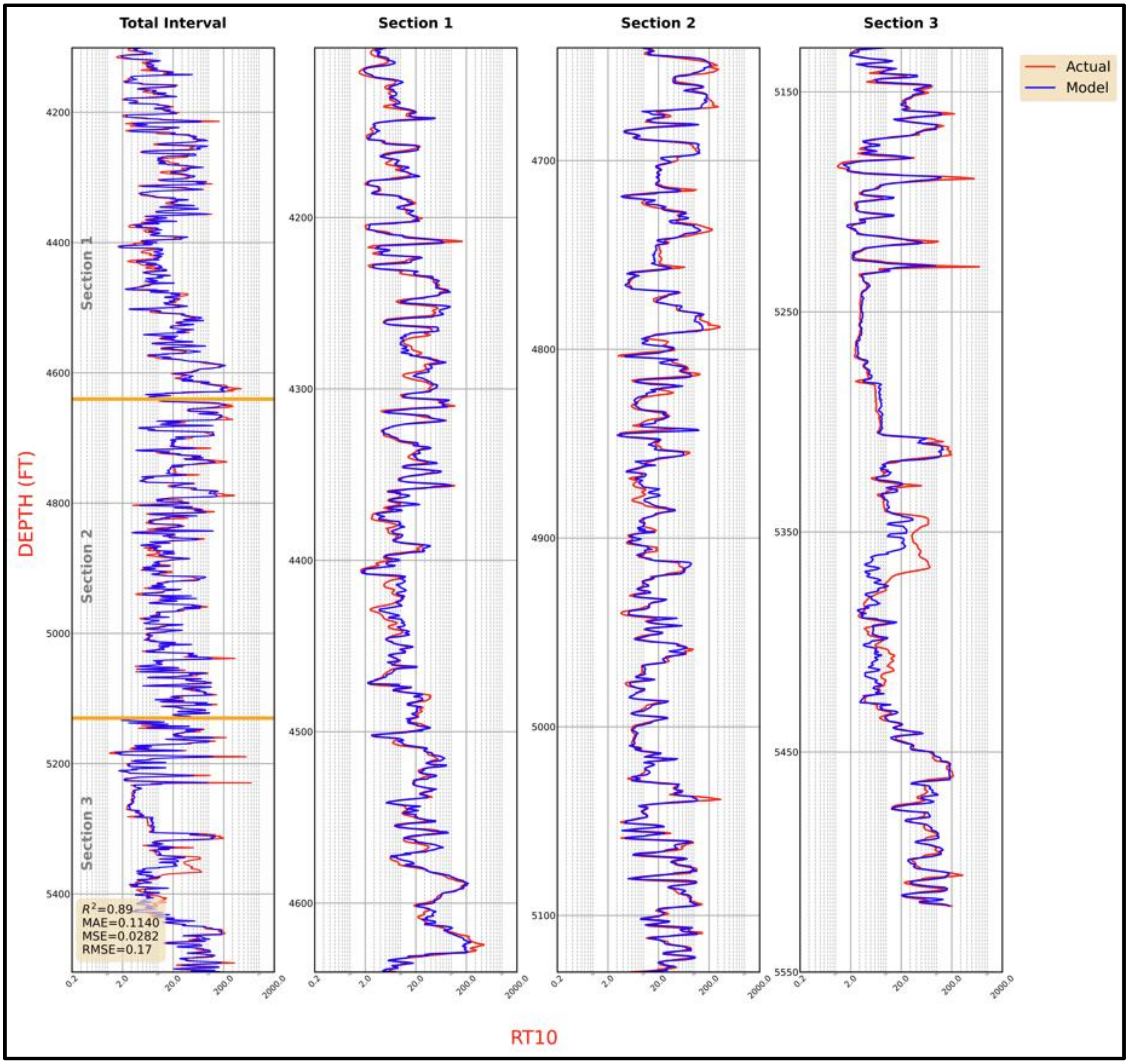

Figure-10: Blind validation, well 22055, RT10 results compared with actual measurements

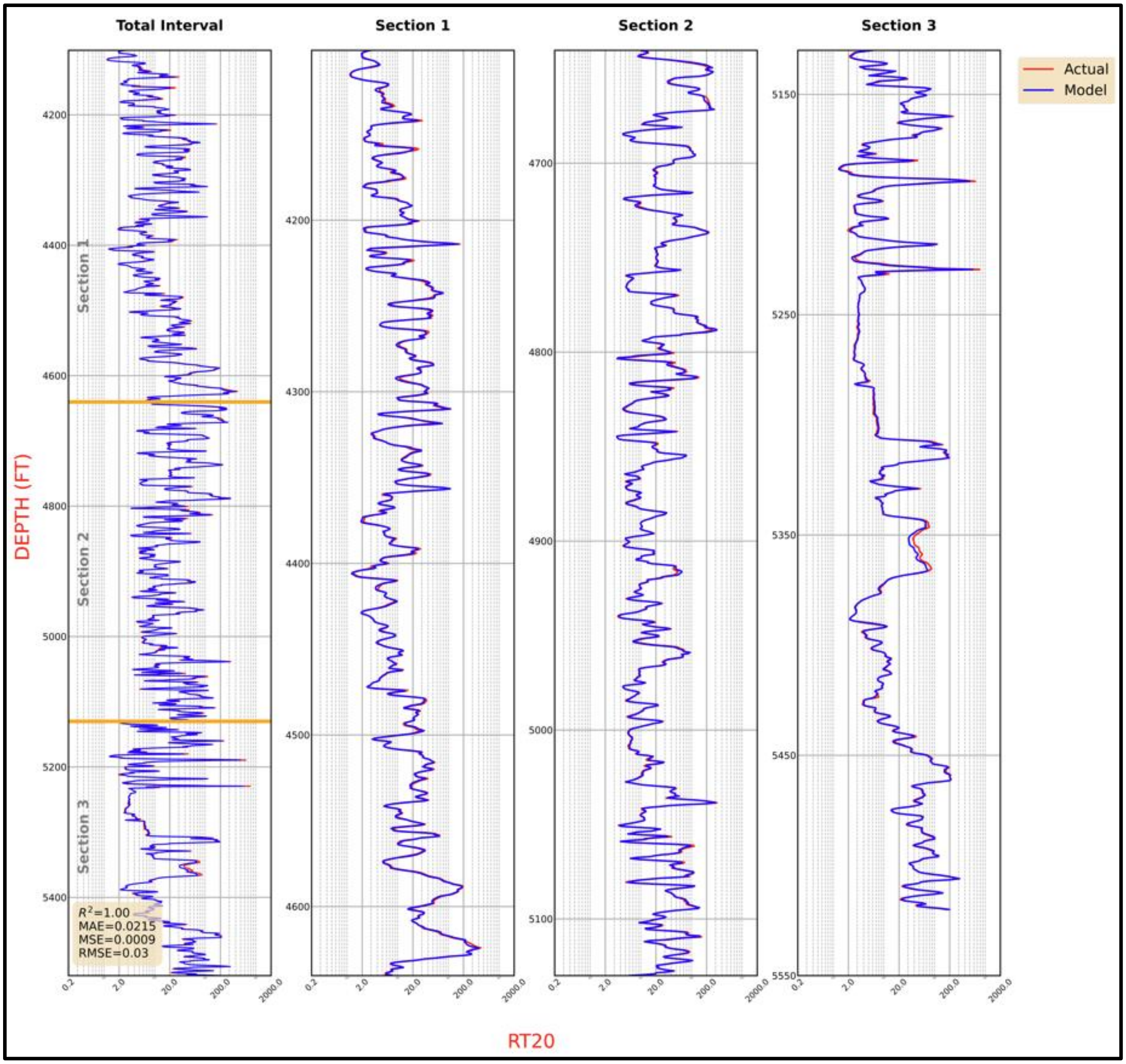

Figure-11: Blind validation, well 22055, RT20 results compared with actual measurements

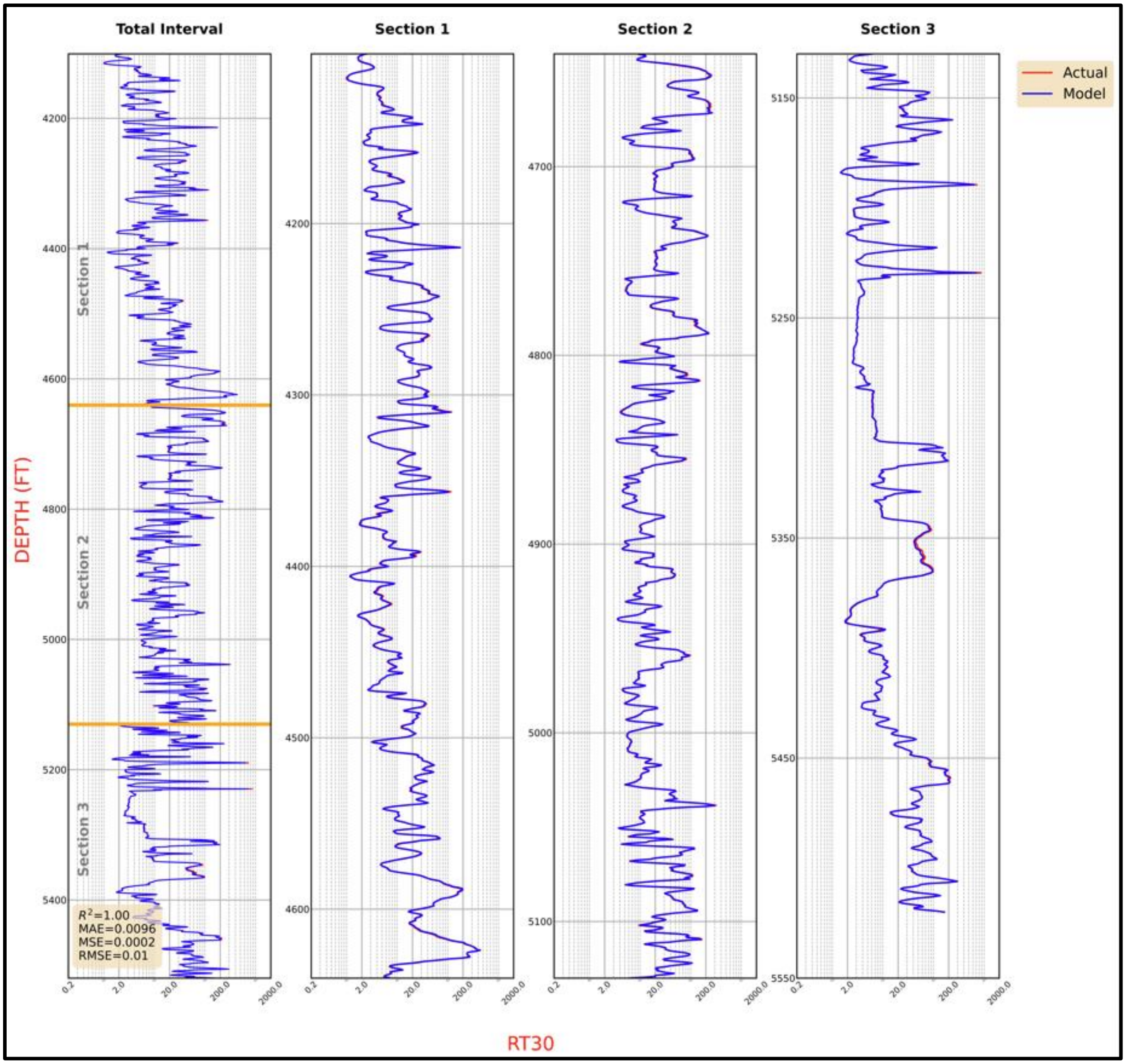

Figure-12: Blind validation, well 22055, RT30 results compared with actual measurements

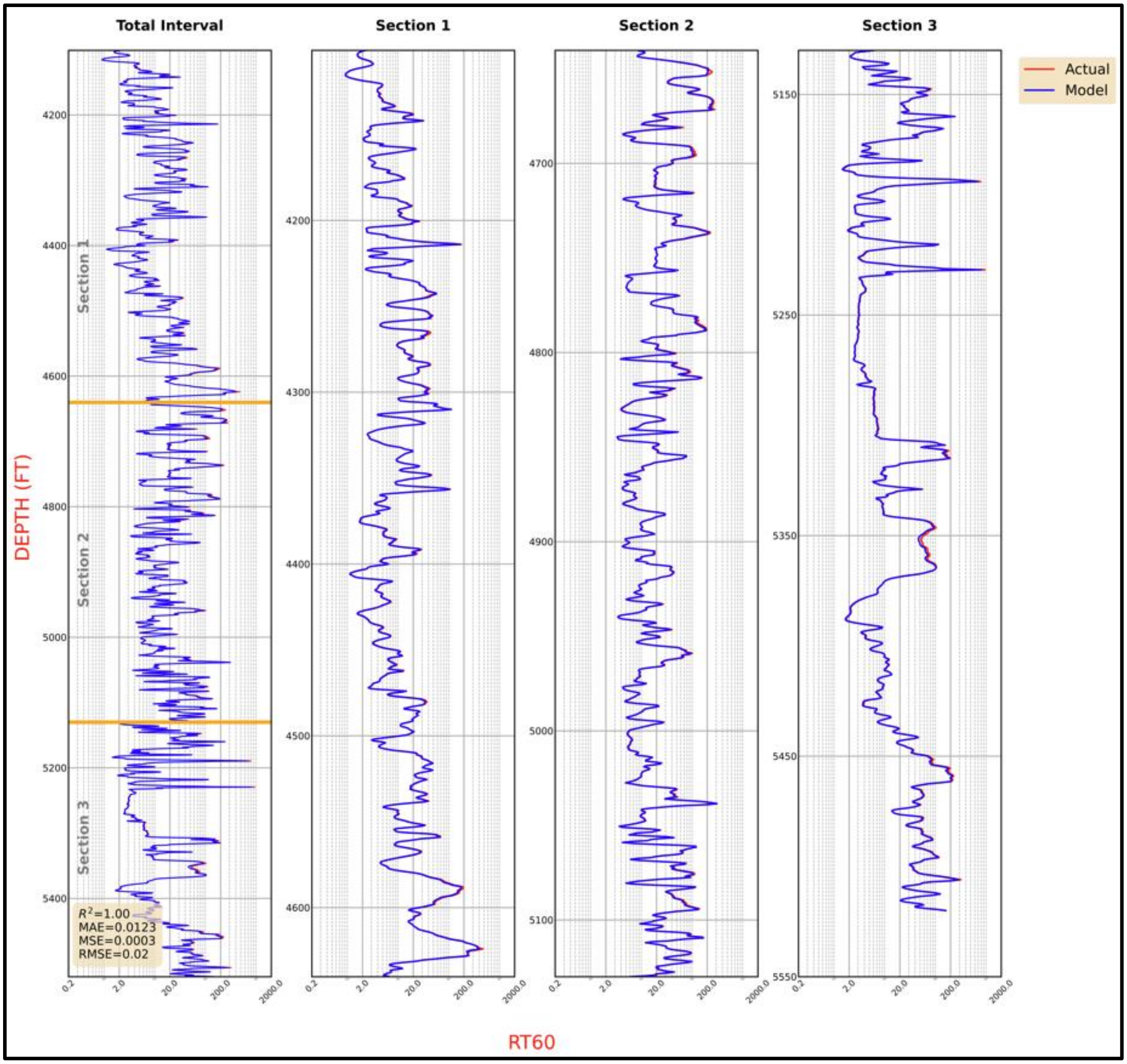

Figure-13: Blind validation, well 22055, RT60 results compared with actual measurements

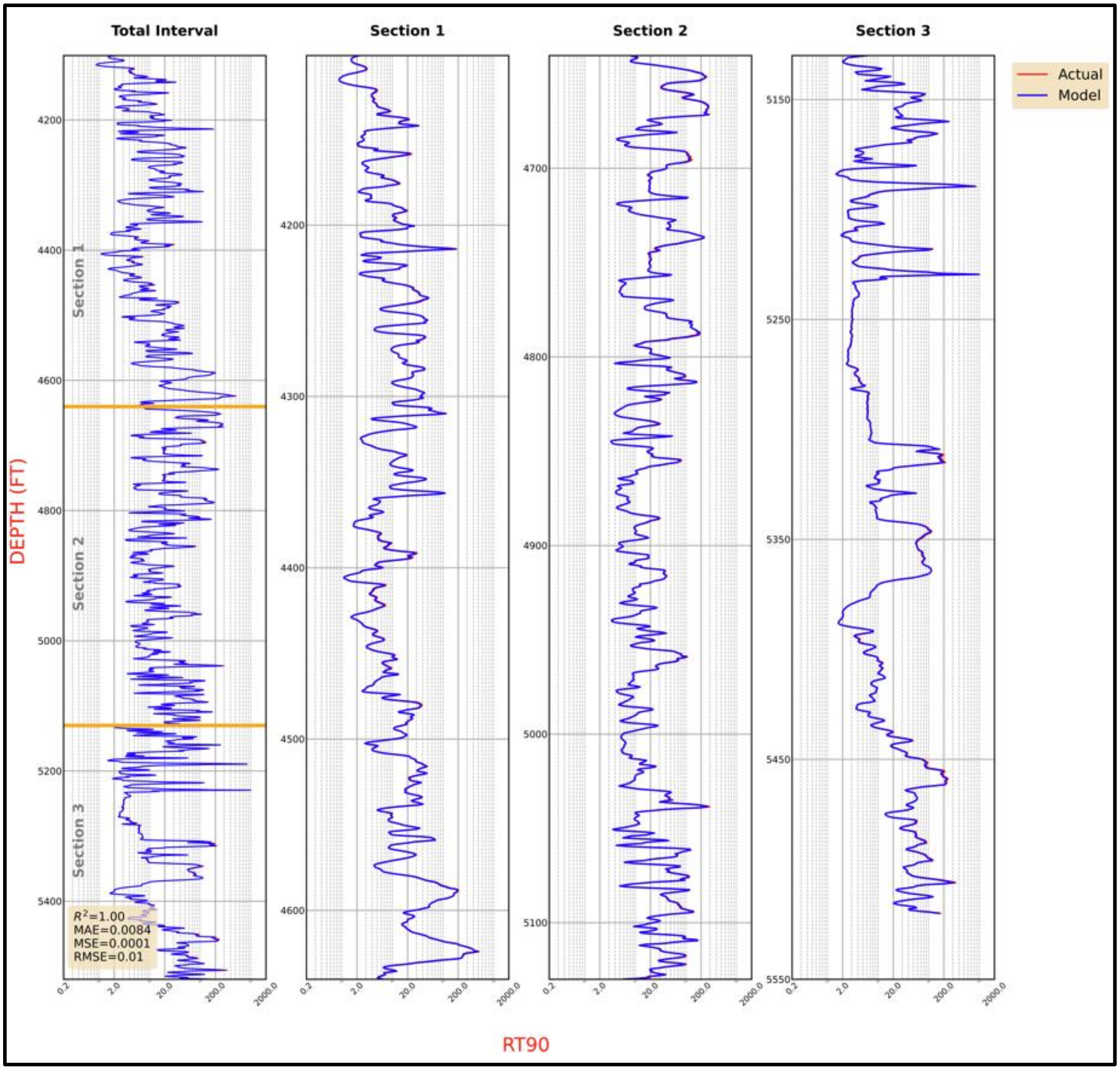

Figure-14: Blind validation, well 22055, RT90 results compared with actual measurements

Enhancing Results

The first two neural network models, which were predicting NPHI and DT, had the lowest performance compared to the other ones due to having least number of features as input for training. To resolve the issue, First ANN1 was retrained by feeding DT and RHOB models as extra features. Then similarly, ANN2 was retrained by feeding NPHI from the retrained ANN1 model plus RHOB and PE models. Figure-15 shows the structure of retraining ANN1 and ANN2.

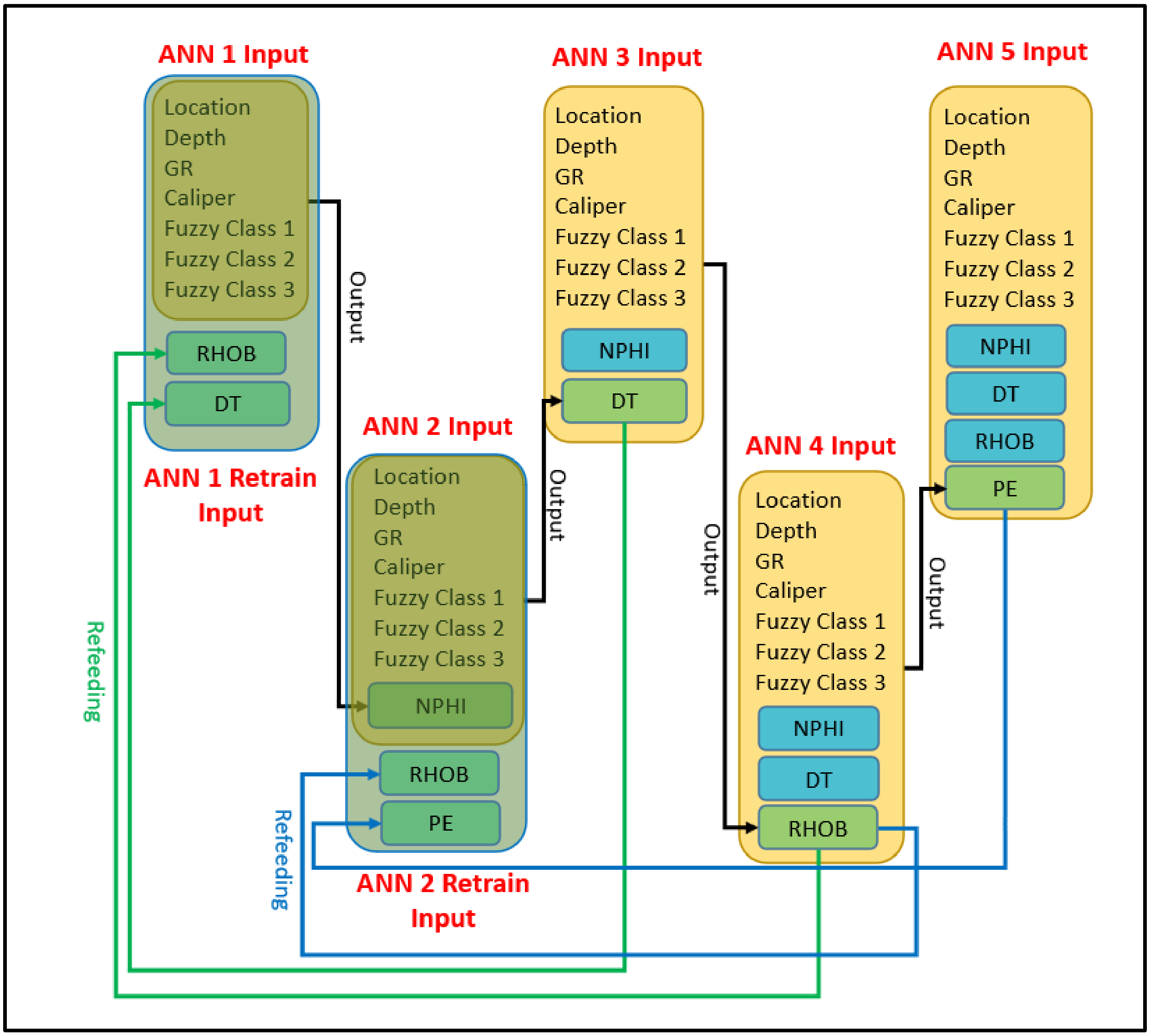

Figure-15: Retraining feature structures of ANN1 and ANN2 to enhance results of NPHI and DT

Figure-16 compares the NPHI predictions before and after enhancement with actual measurements. Going through the details of the enhanced prediction, its pattern recognition shows improvement resulting in 95% accuracy.

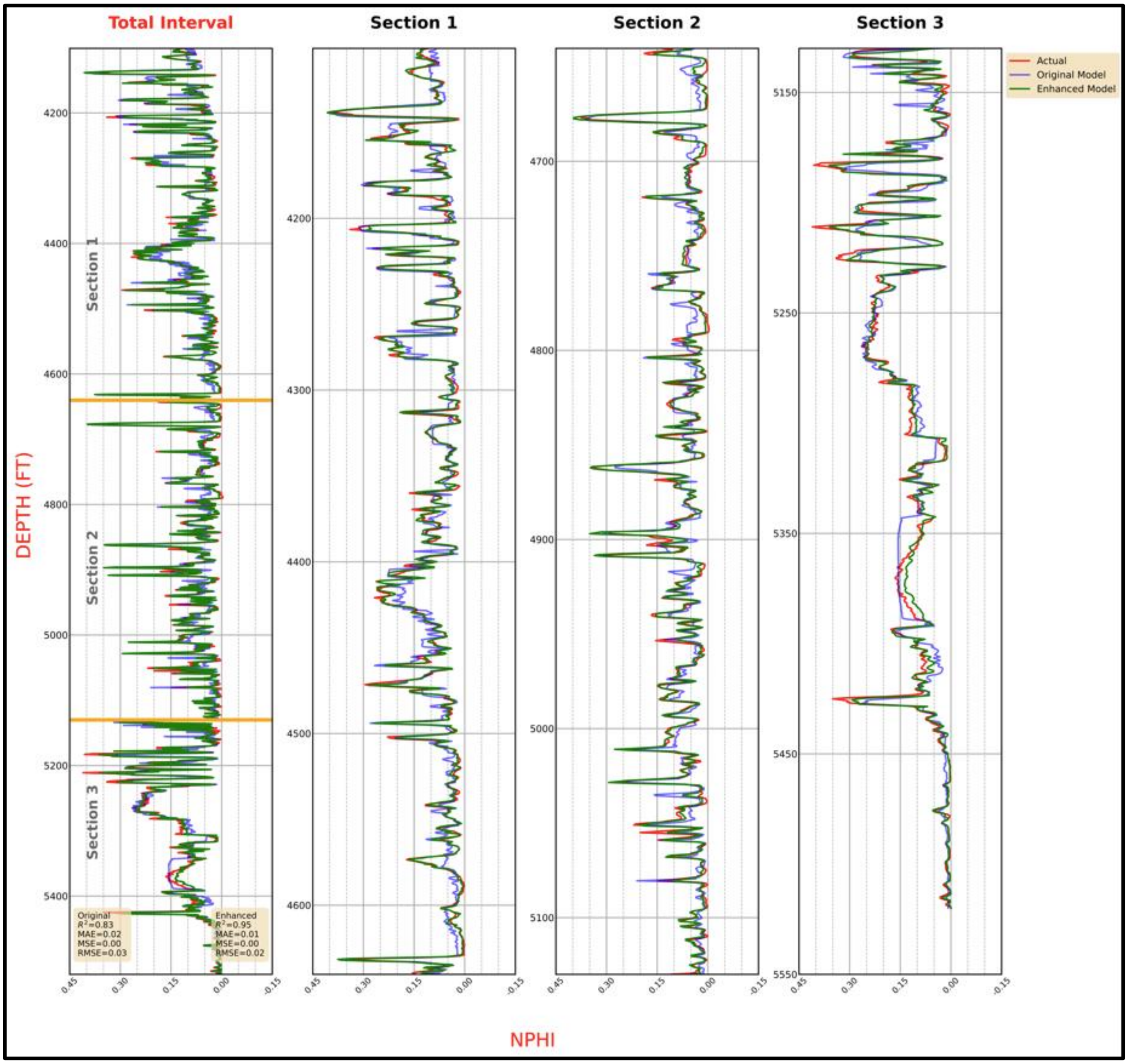

Figure-16: Enhancement results of NPHI on blind validation, well 22055

Similarly, in Figure-17, the enhanced model predicts DT slightly better however where DT is high due to Cycle Skipping and/or shale presence not much improvement is observed.

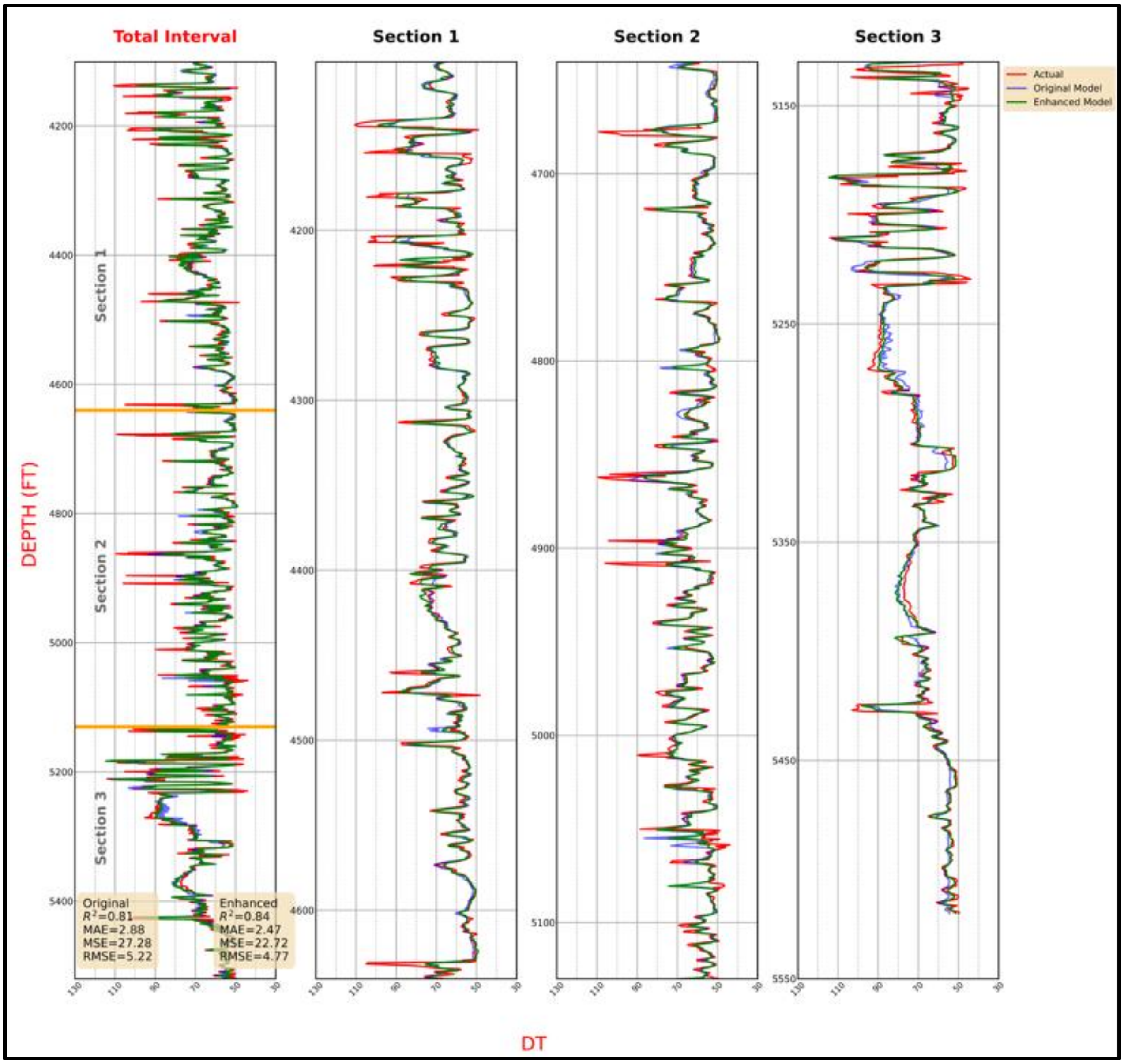

Figure-17: Enhancement results of DT on blind validation, well 22055

As NPHI and DT retraining enhanced the results, ANN3 was retrained with new NPHI and DT to improve results of RHOB. Figure-18 shows the RHOB enhancement results.

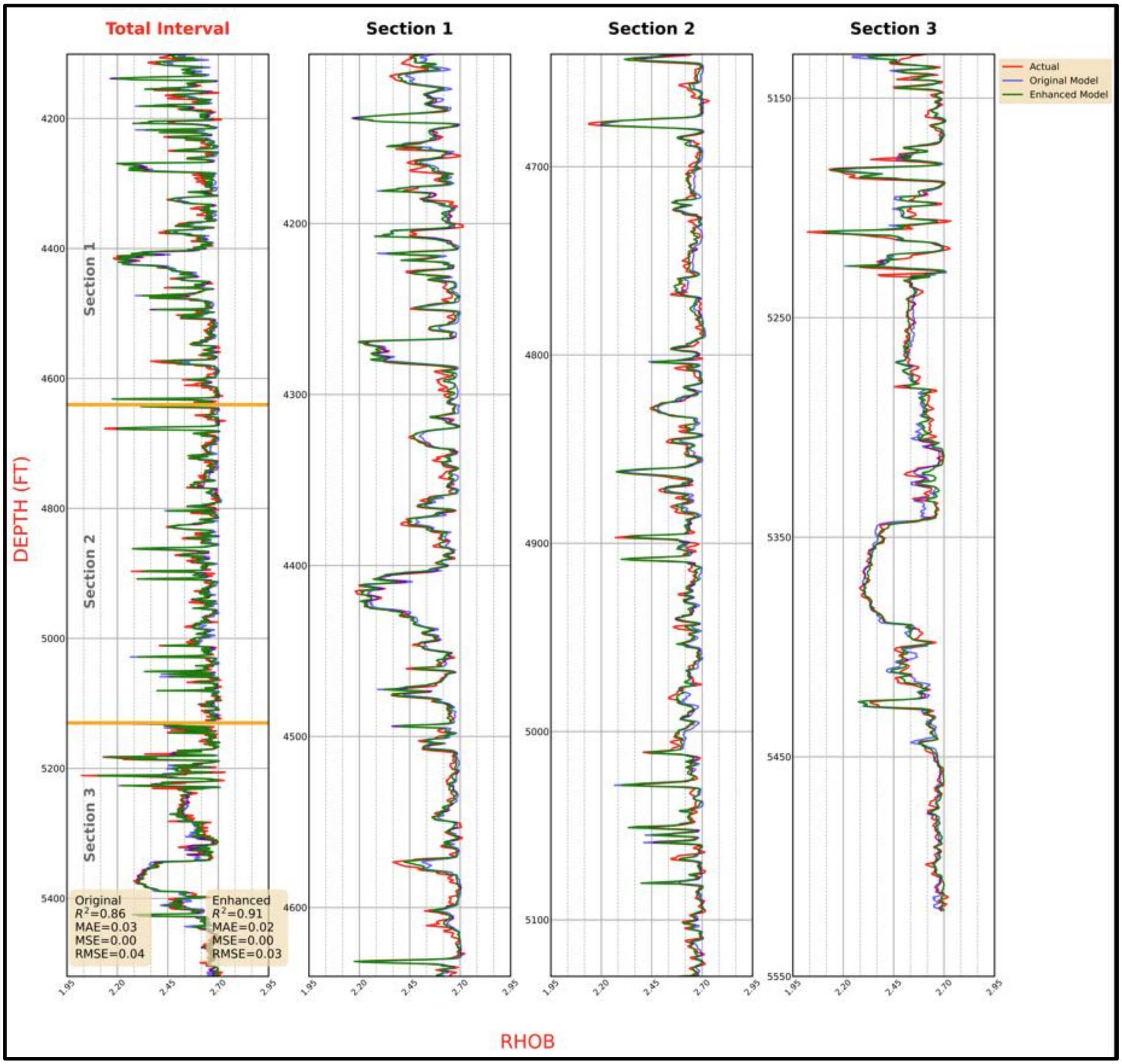

Figure-18: Enhancement results of RHOB on blind validation, well 22055

Finally, ANN4 was retrained to enhance PE results, which did not improve, and the accuracy of predictions for PE remained at 85% (Figure-9).

Conclusions

In order to have a successful sequential modeling two main challenges had to be addressed at the beginning. First, the order of modeling which was achieved by using Fuzzy Set Theory technique, KPI; and second generating features (inputs) at early stages where not much information was available. To overcome this problem, Fuzzy Clustering provided better and faster solutions.

On contrary of common misperception that an efficient Artificial Neural Network significantly depends on its architecture and hyperparameter tuning, a successful modeling dominantly depends on data itself and feature generation based on domain expertise without any assumptions, interpretations, simplifications, and biases. This study allocated minimal effort and time on hyperparameters tuning (only was done on the first ANN sequence) is a good example.

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Appendix

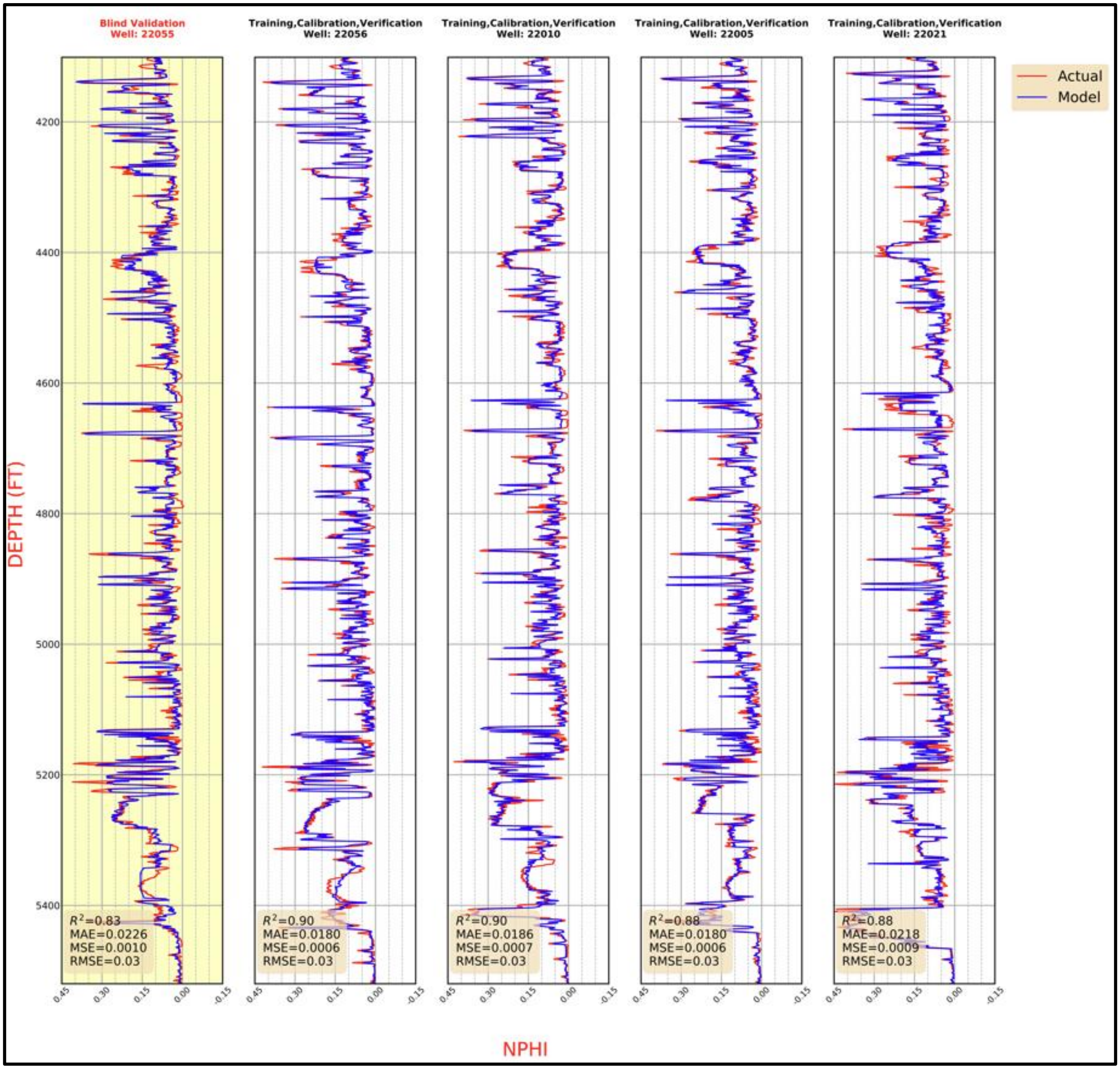


Figure A-1: Results of ANN1, NPHI model, Part 1

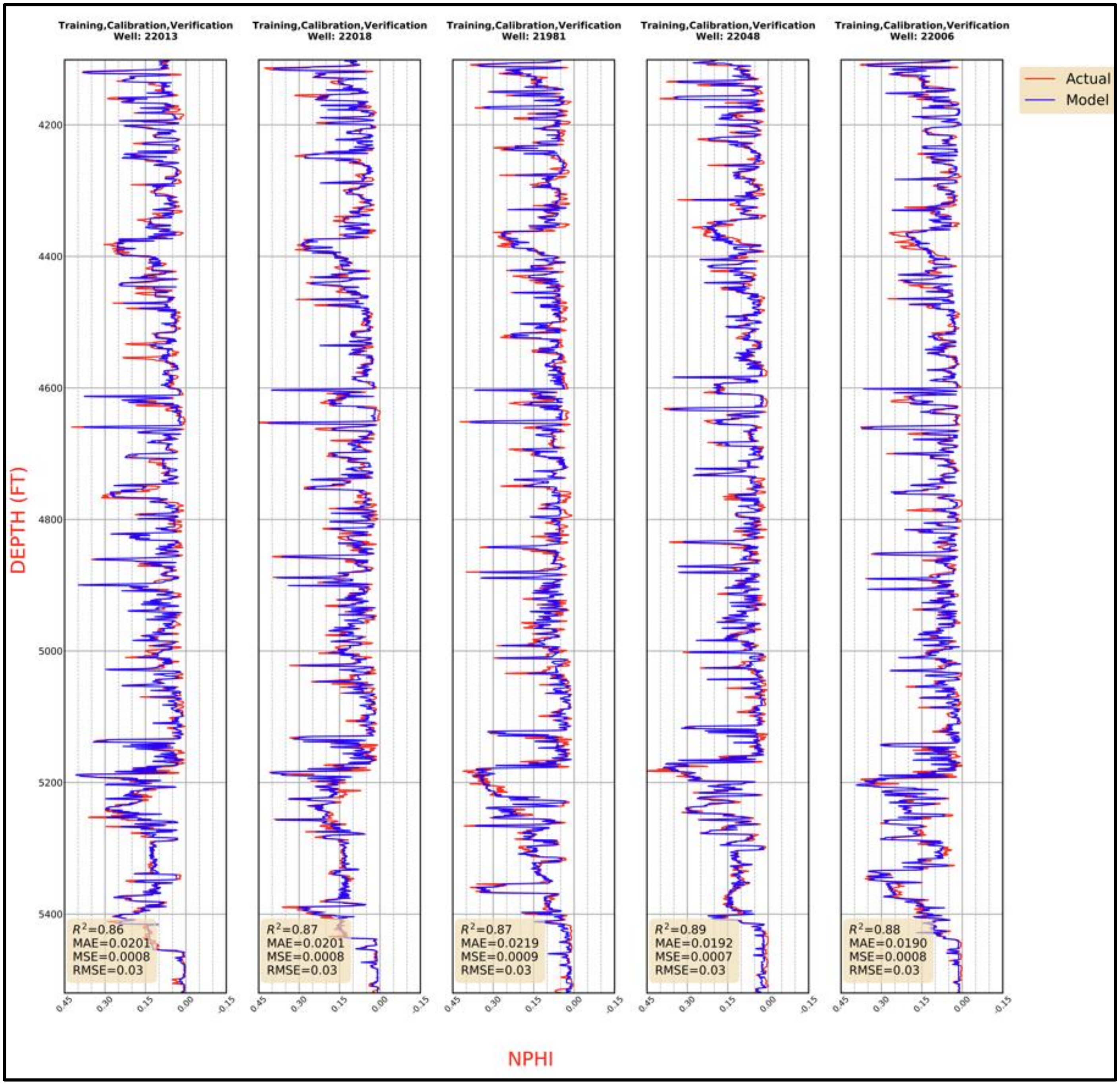


Figure A-2: Results of ANN1, NPHI model, Part 2

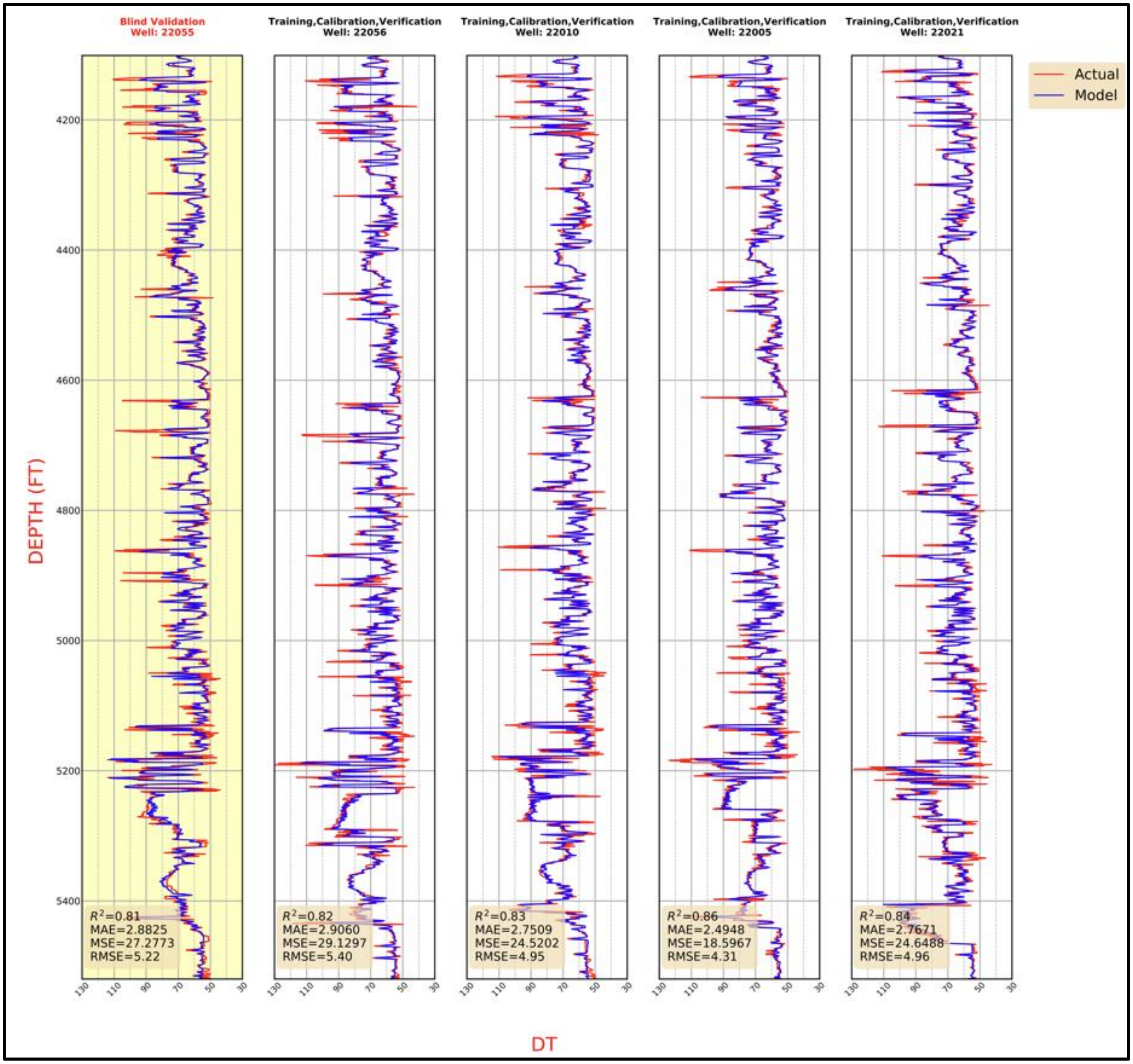


Figure A-3: Results of ANN2, DT model, Part 1

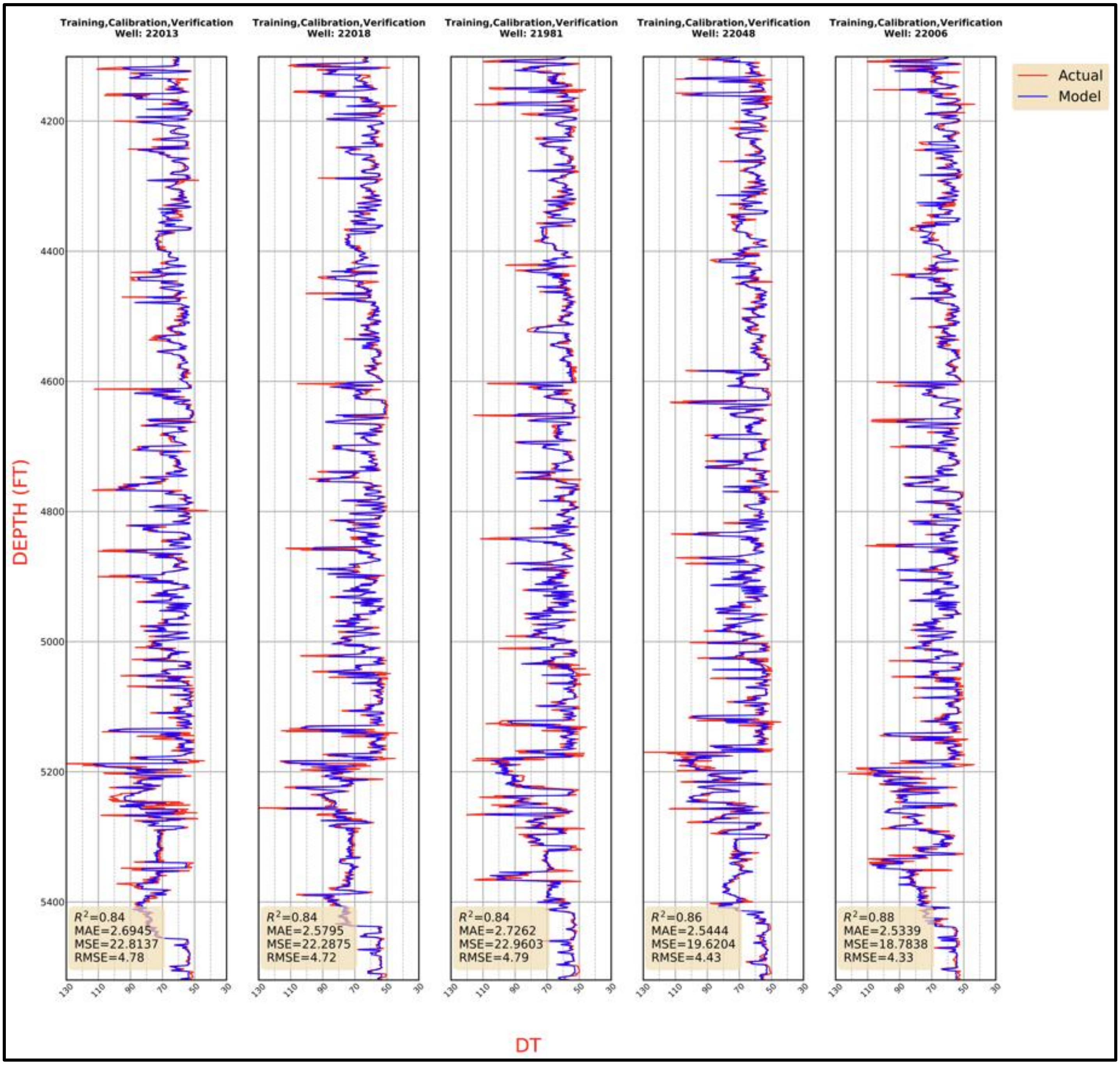


Figure A-4: Results of ANN2, DT model, Part 2

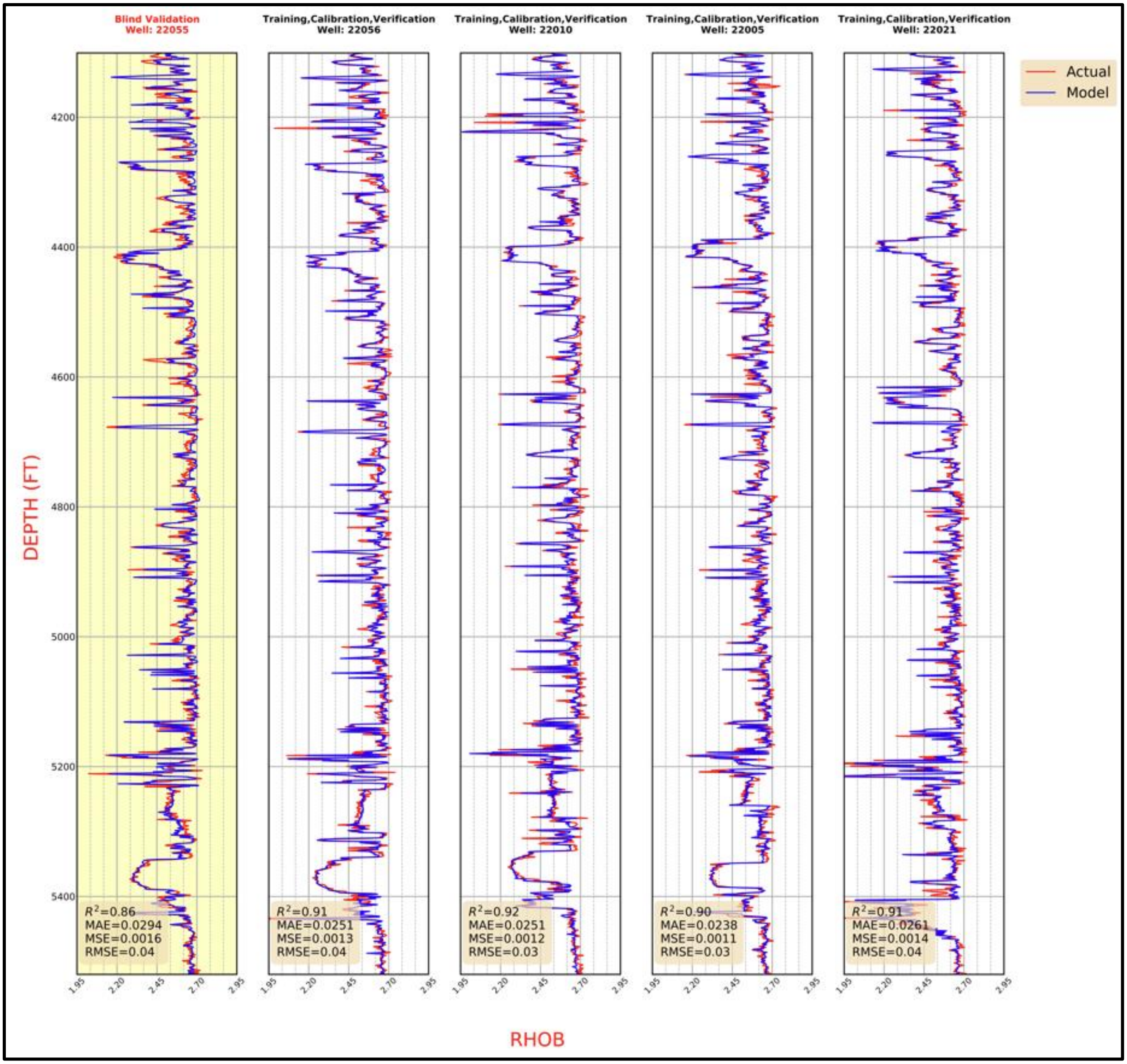


Figure A-5: Results of ANN3, RHOB model, Part 1

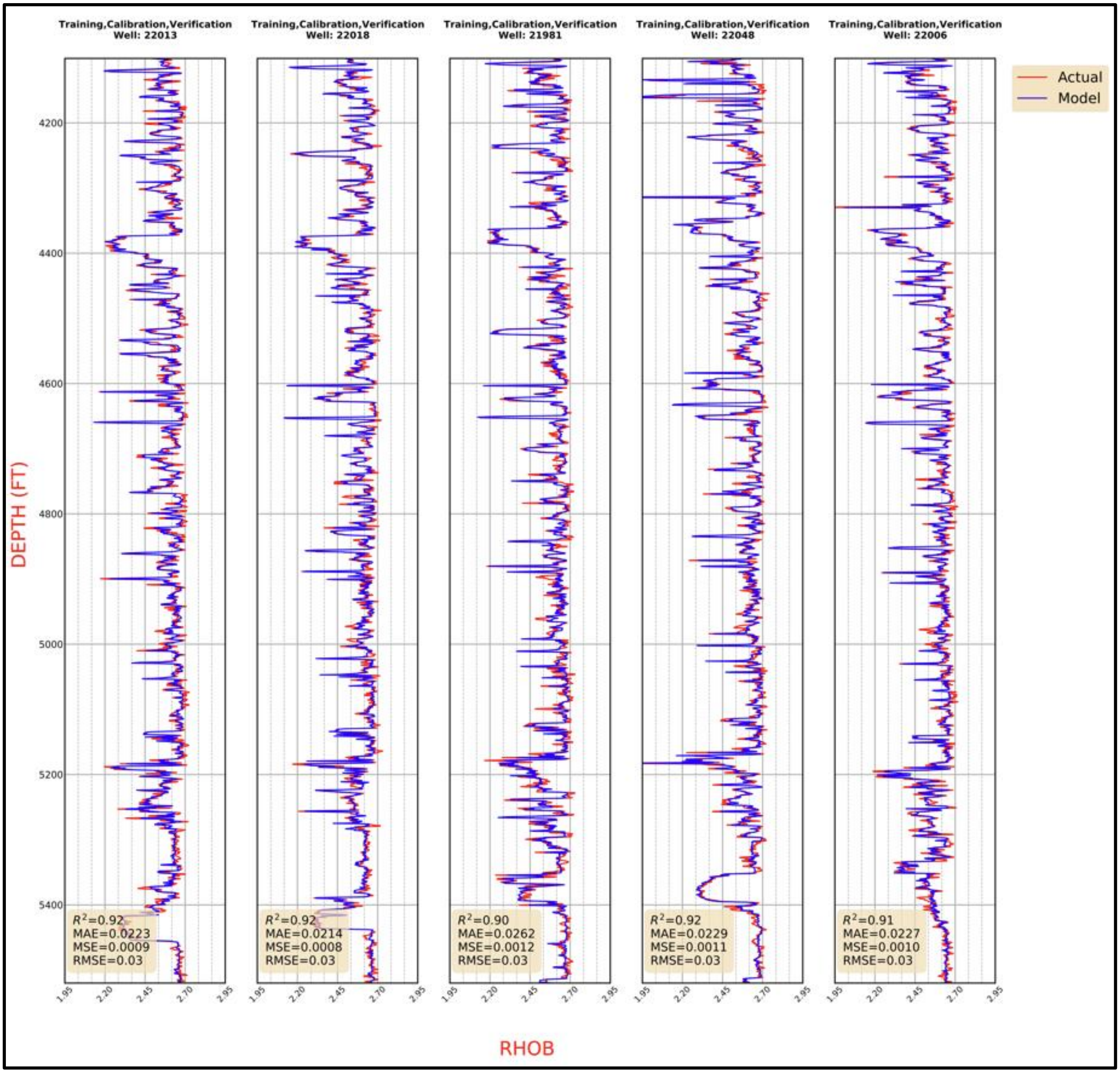


Figure A-6: Results of ANN3, RHOB model, Part 2

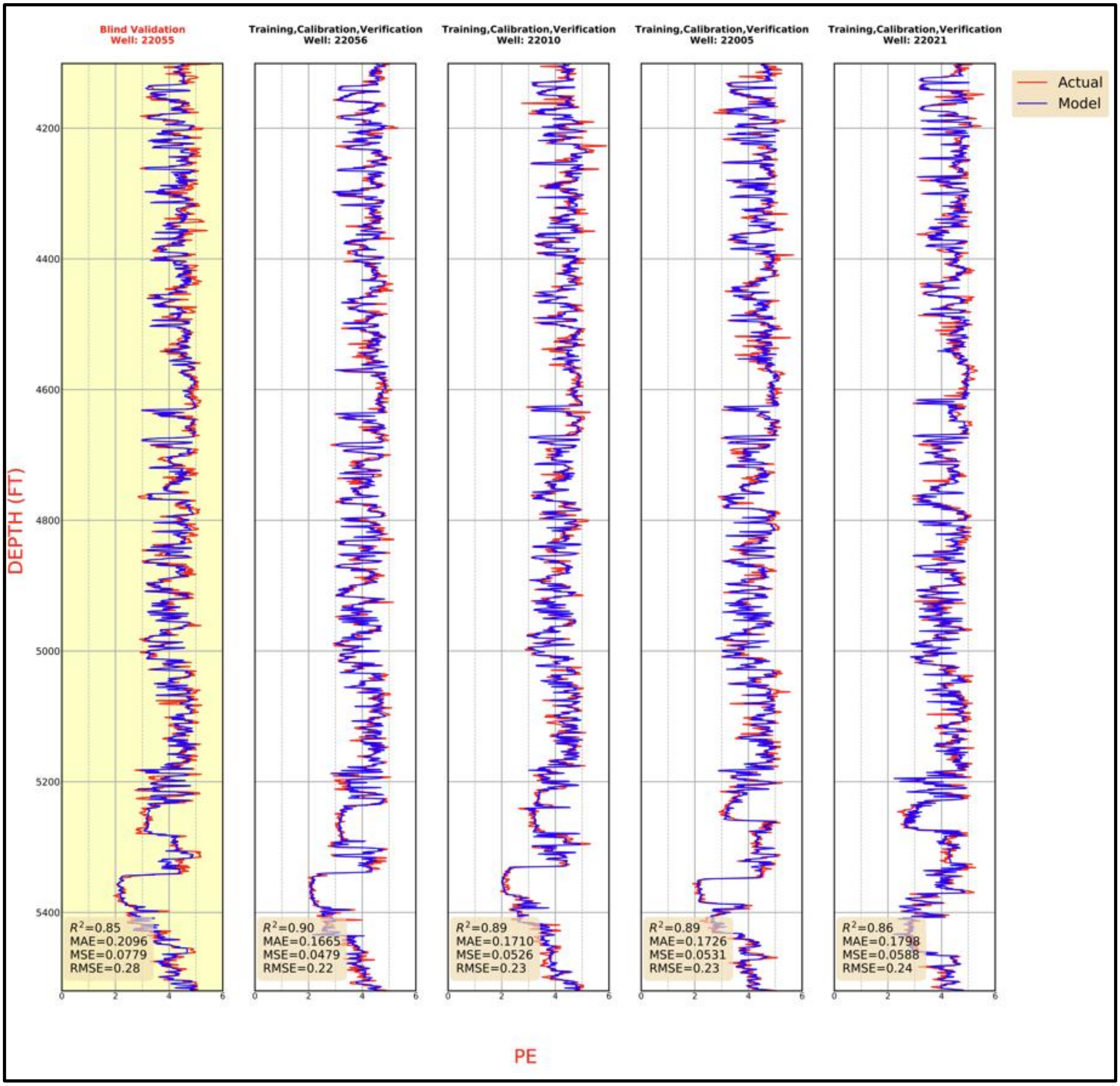


Figure A-7: Results of ANN4, PE model, Part 1

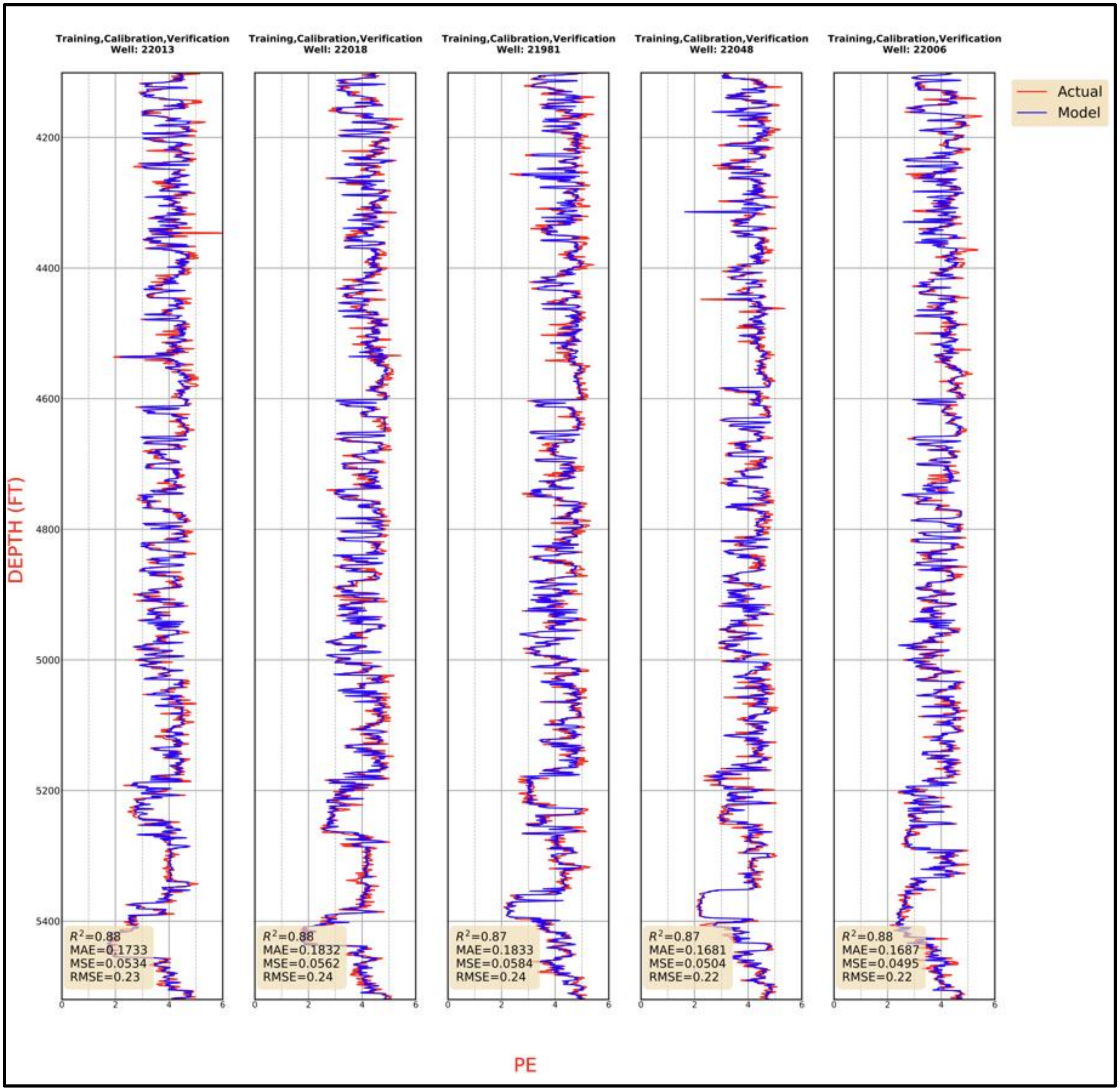


Figure A-8: Results of ANN4, PE model, Part 2

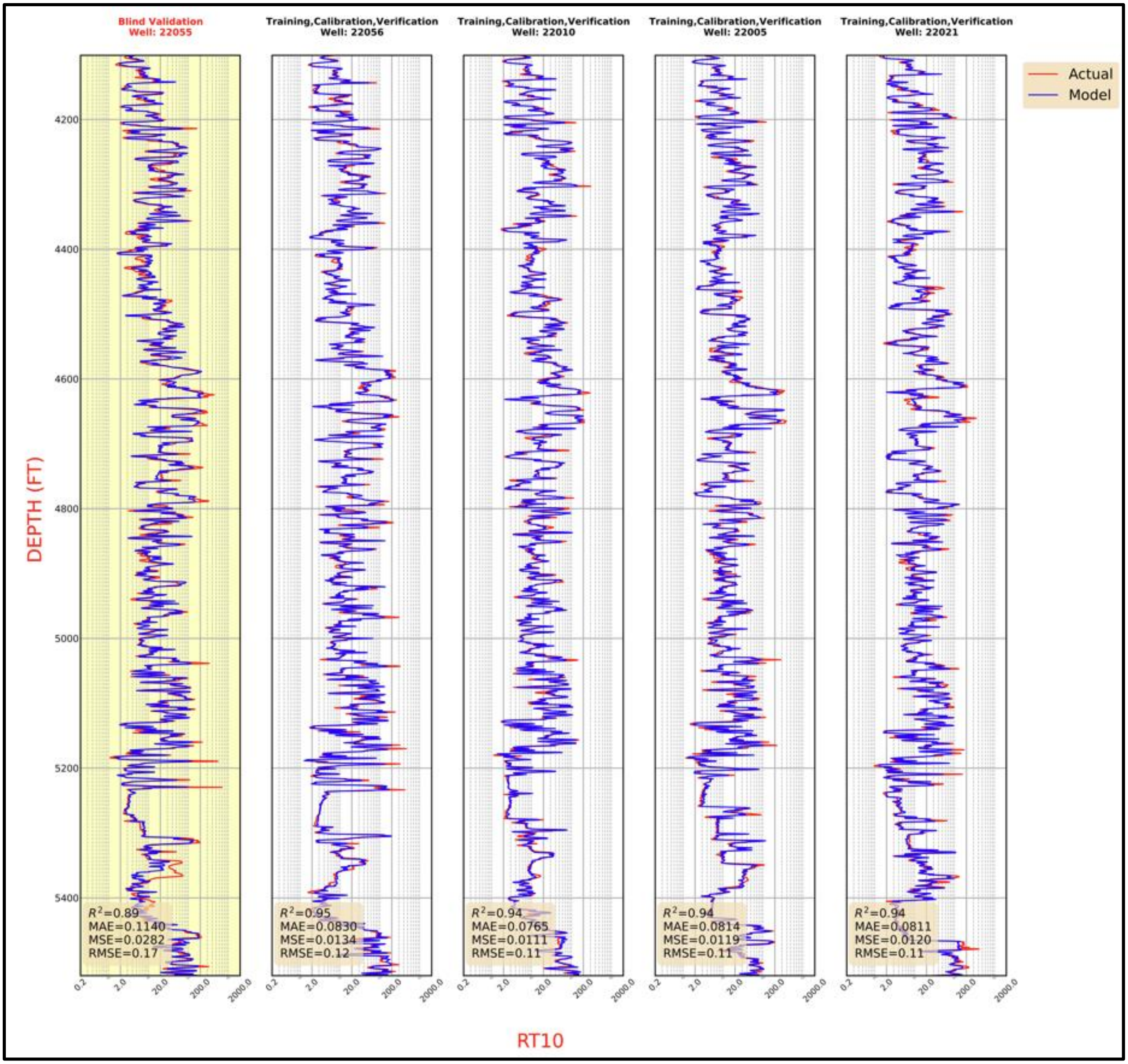


Figure A-9: Results of ANN5, RT10 model, Part 1

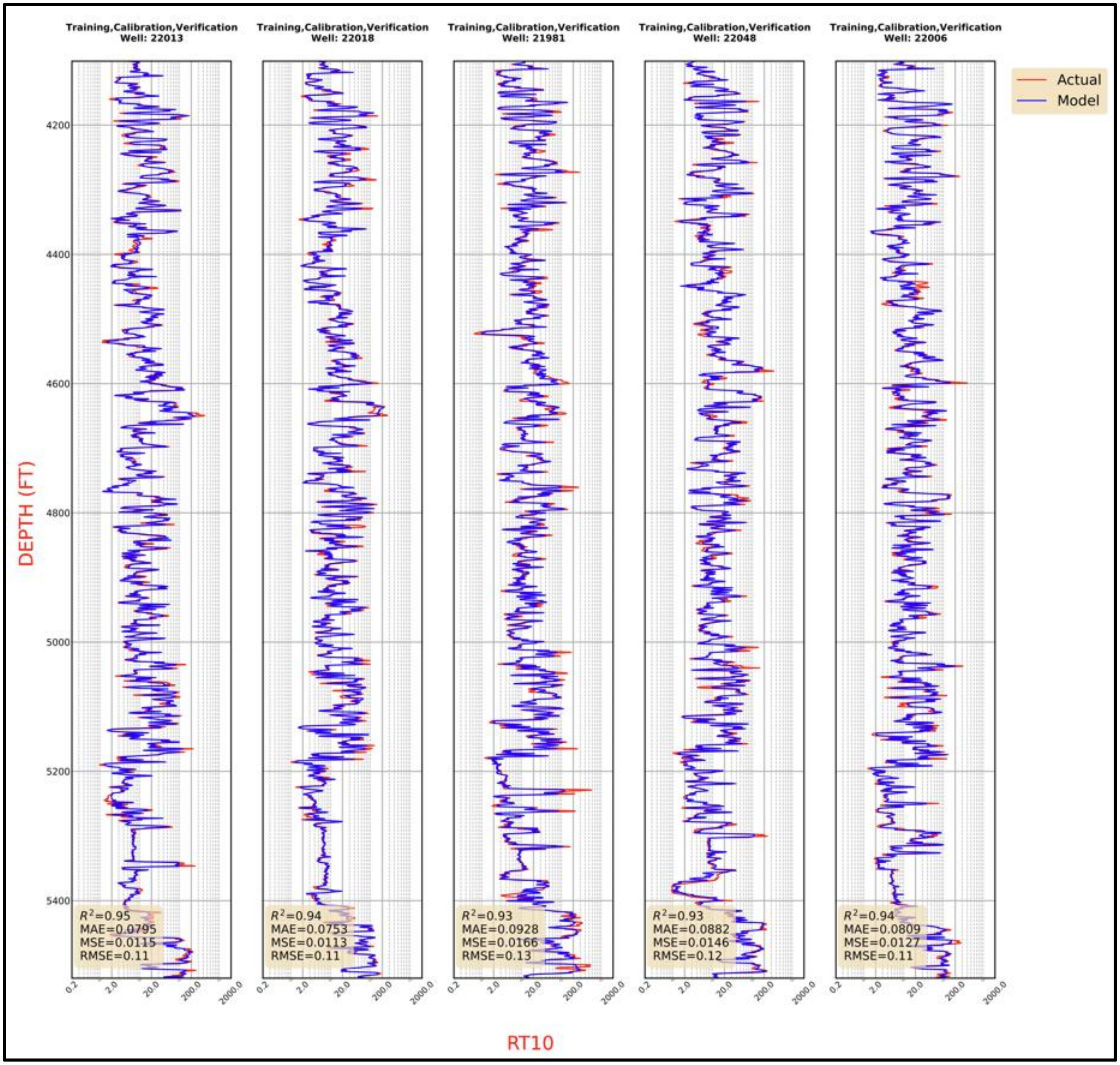


Figure A-10: Results of ANN5, RT10 model, Part 2

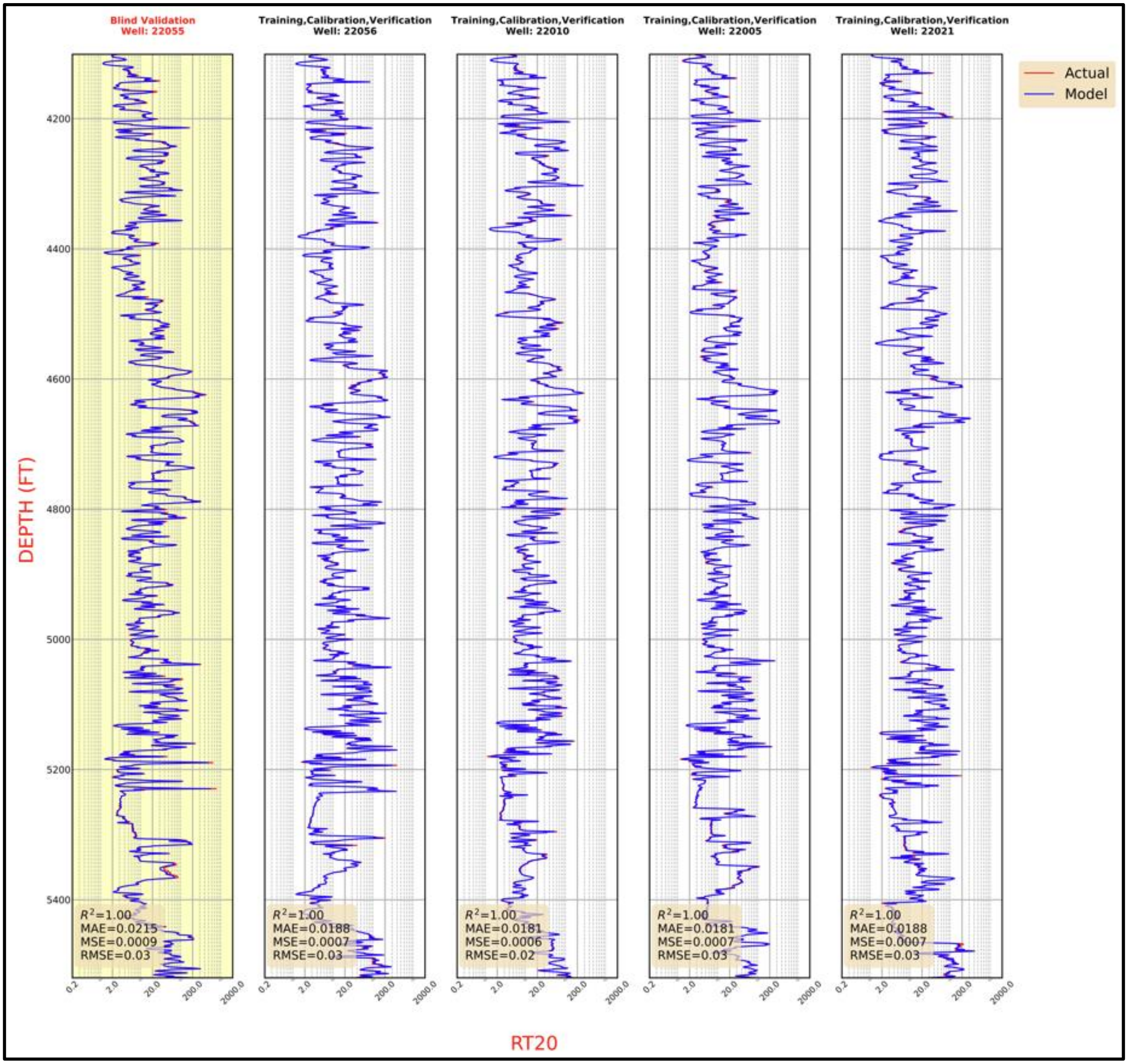


Figure A-11: Results of ANN6, RT20 model, Part 1

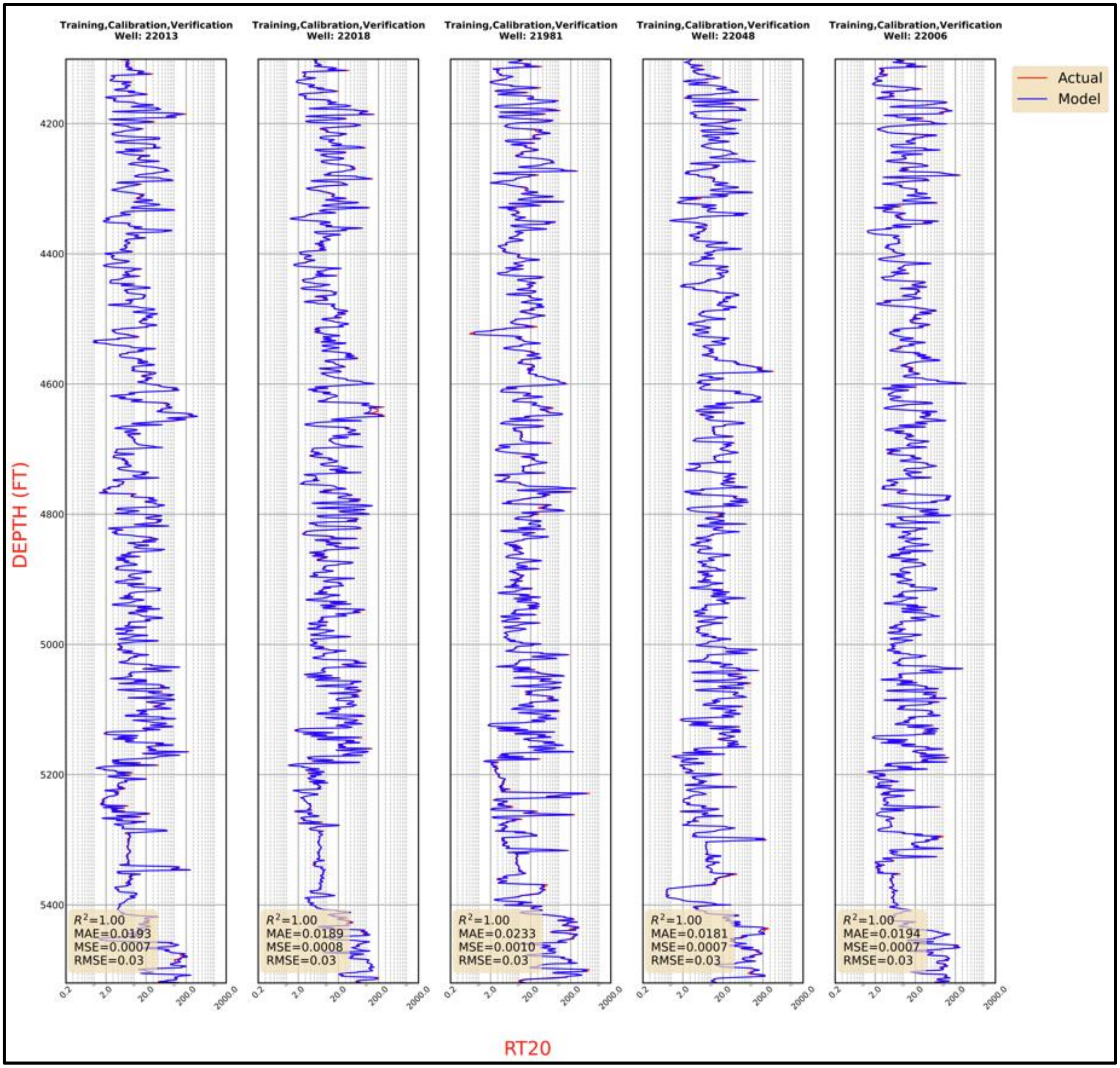


Figure A-12: Results of ANN6, RT20 model, Part 2

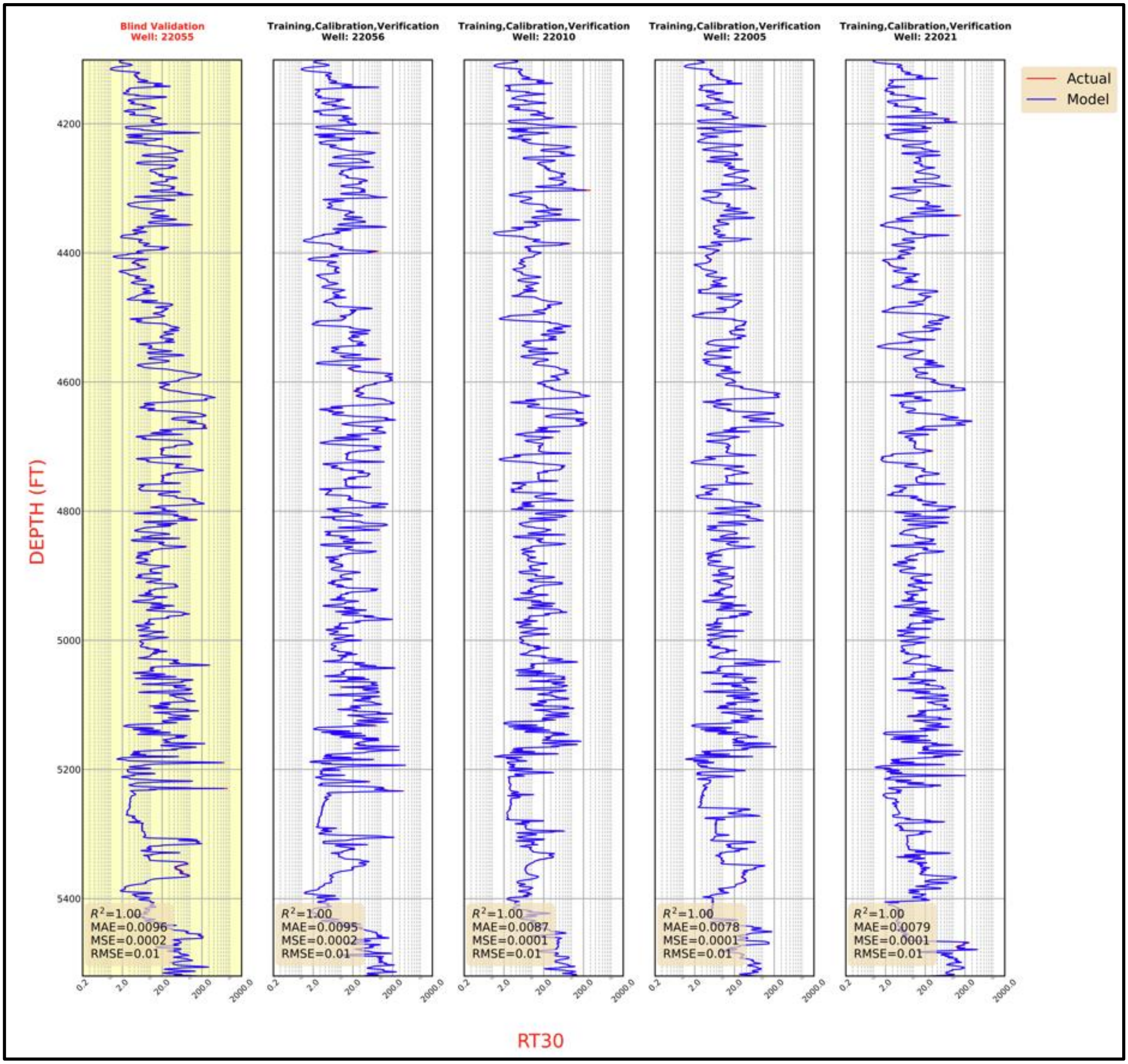


Figure A-13: Results of ANN7, RT30 model, Part 1

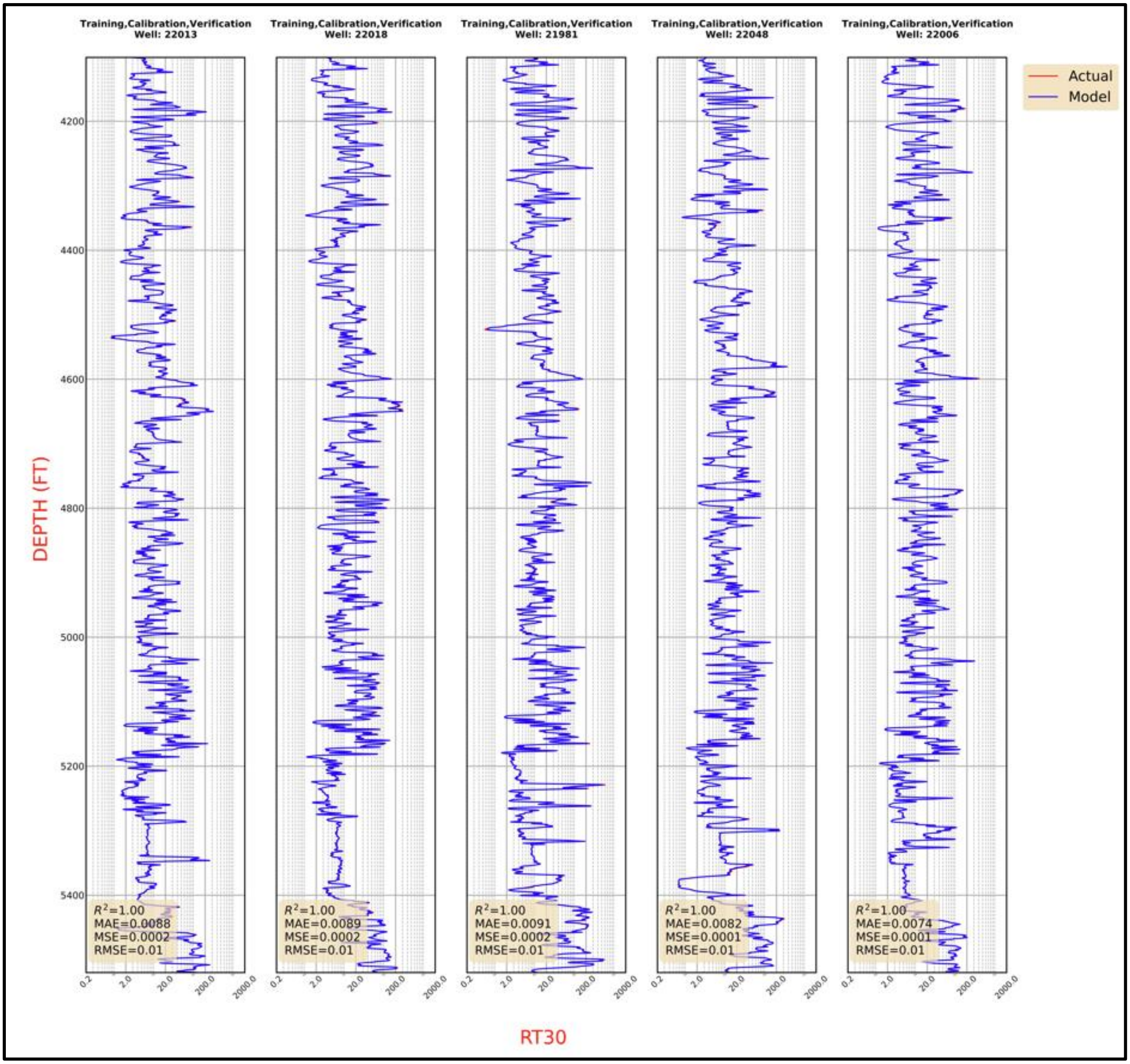


Figure A-14: Results of ANN7, RT30 model, Part 2

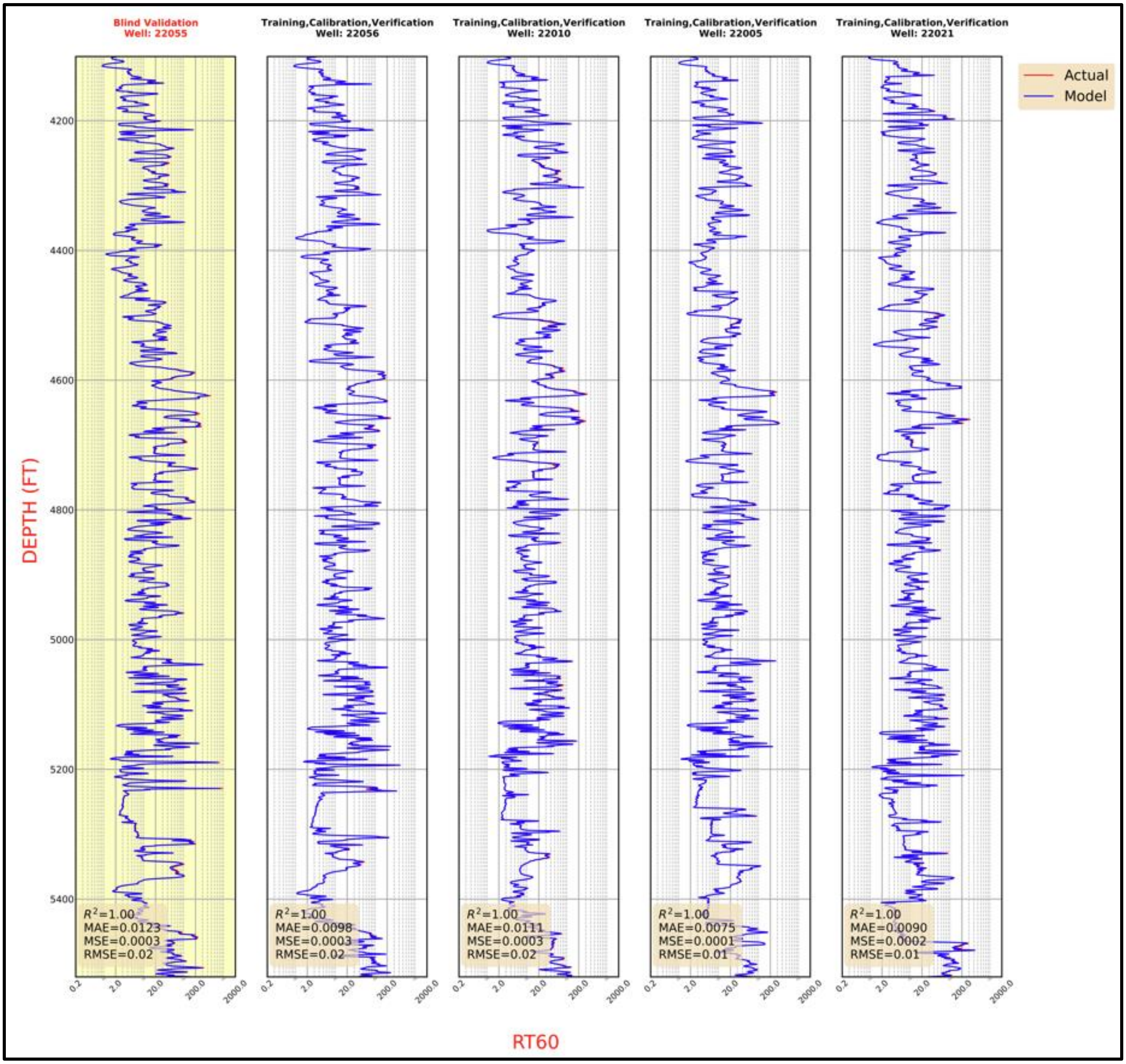
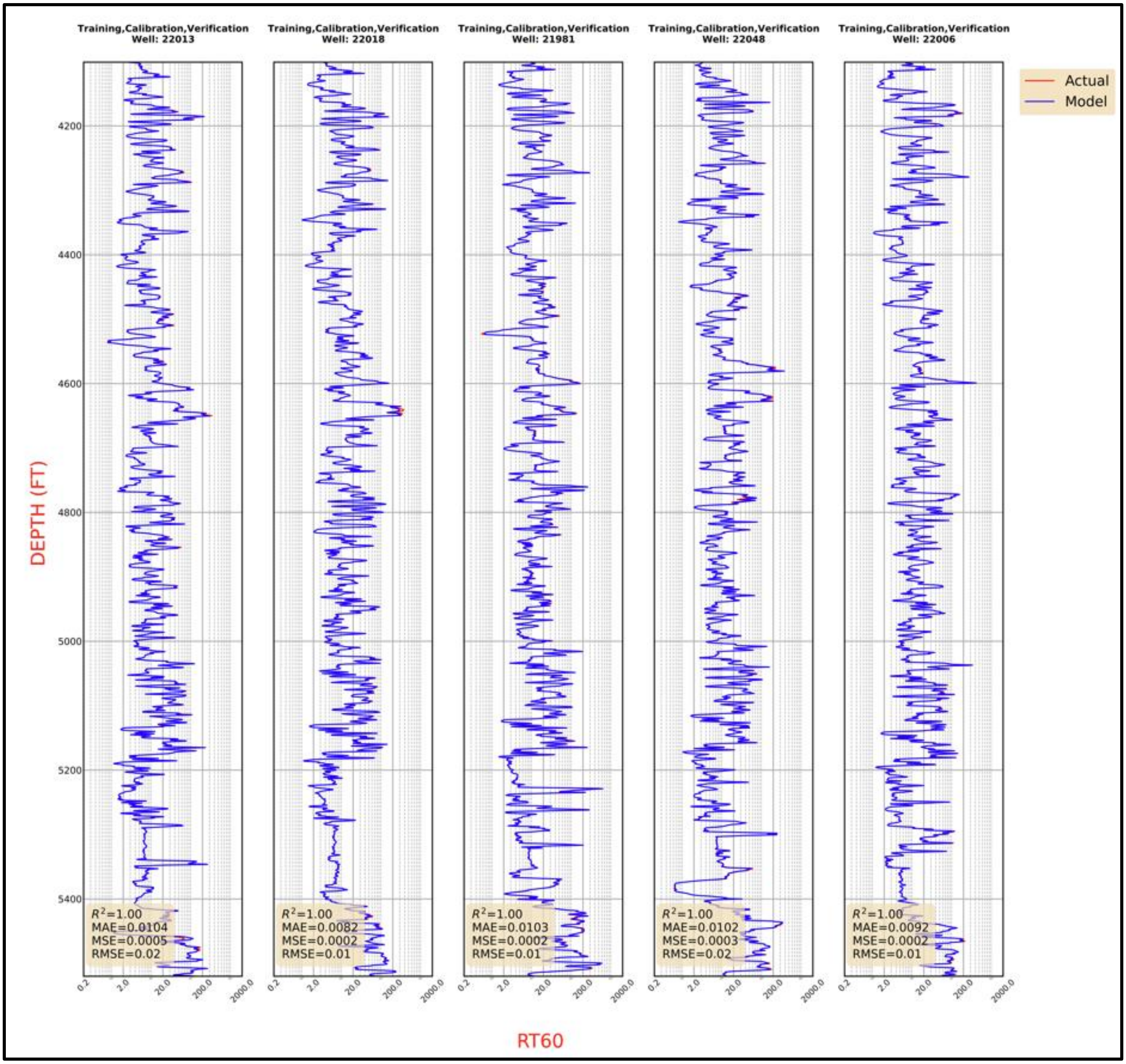


Figure A-15: Results of ANN8, RT60 model, Part 1



igure A-16: Results of ANN8, RT60 model, Part 2

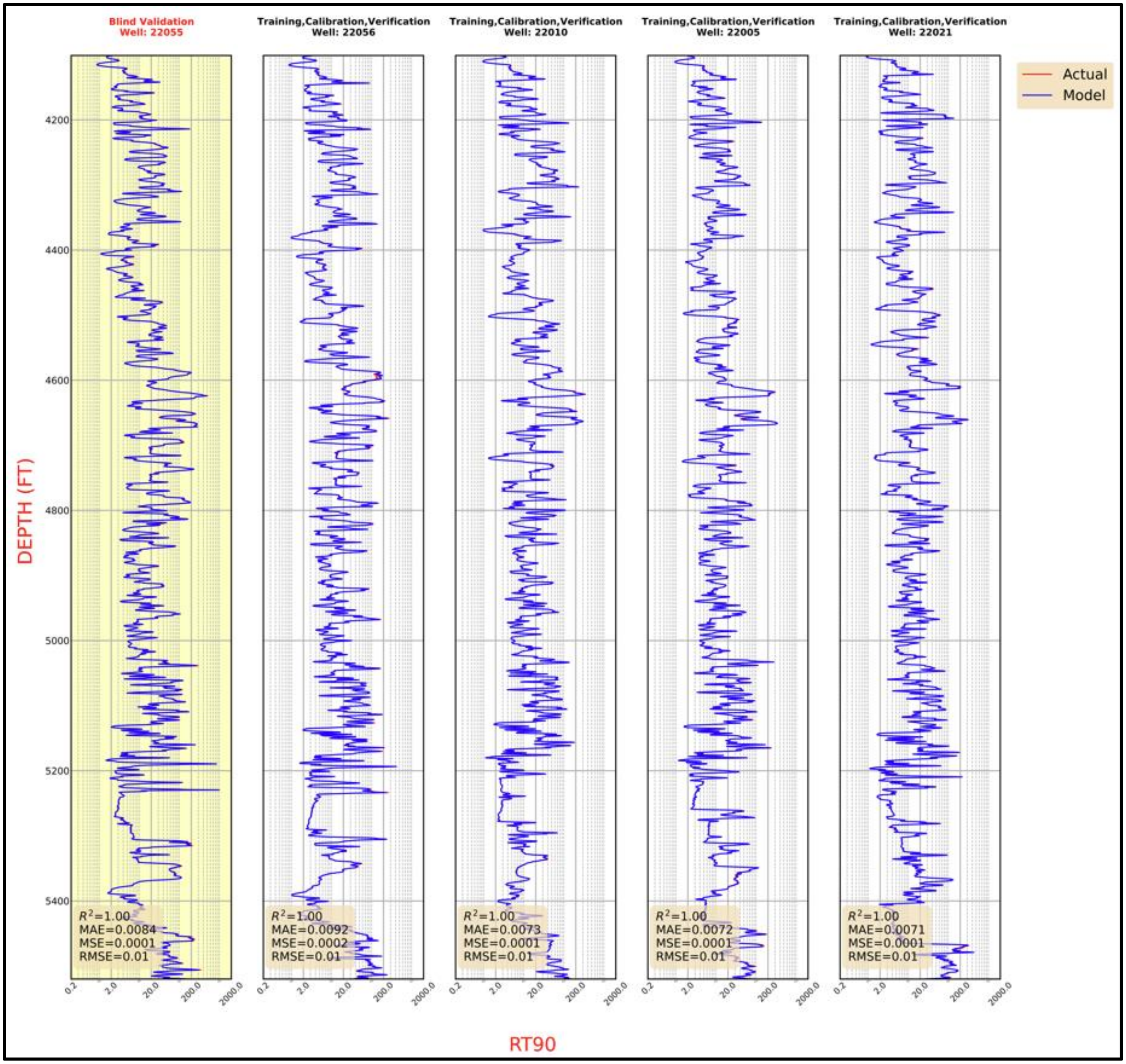


Figure A-17: Results of ANN9, RT90 model, Part 1

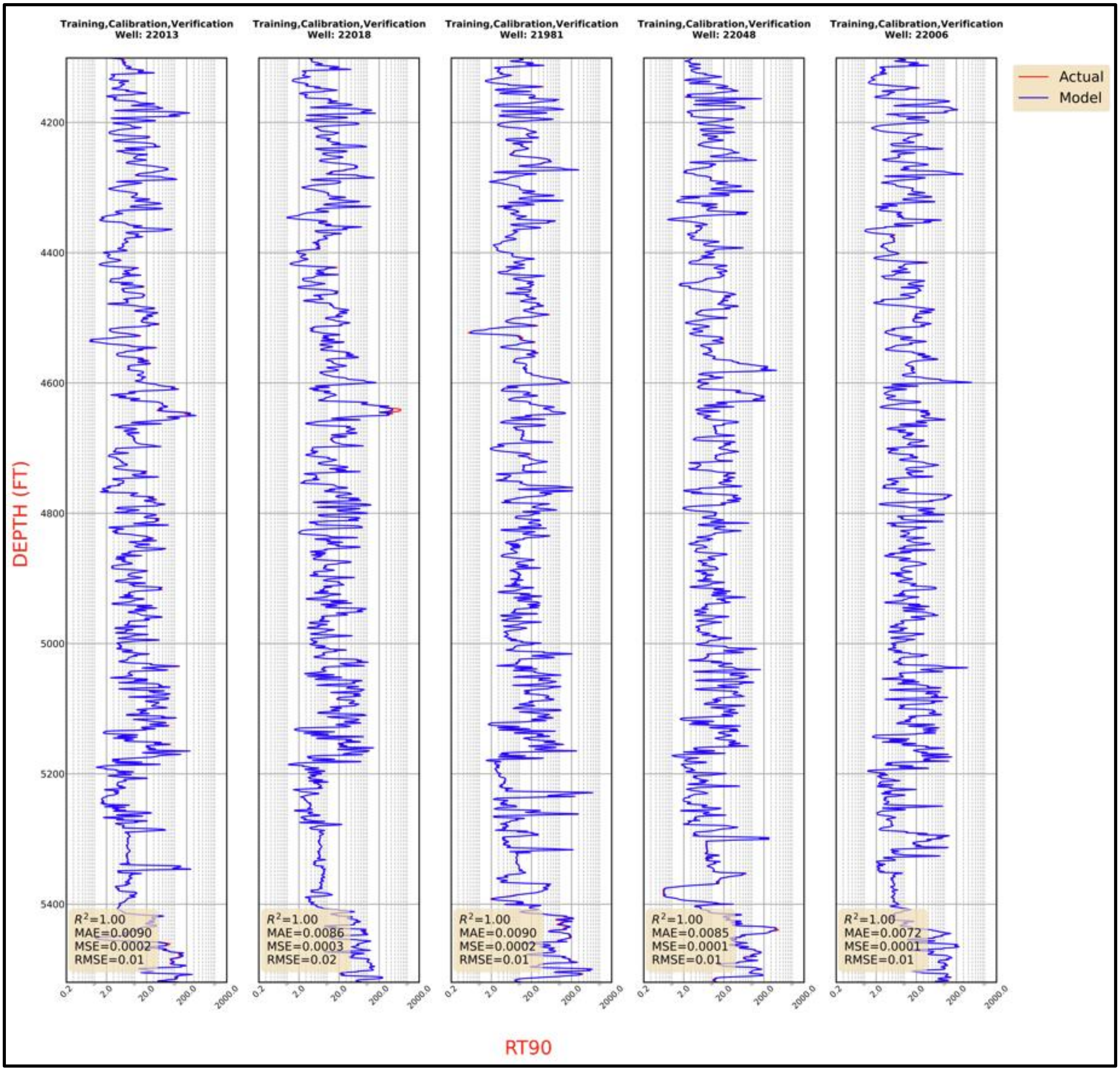


Figure A-18: Results of ANN9, RT90 model, Part 2