

**SCIENTIFIC MACHINE LEARNING FOR
MICROSEISMIC HYPOCENTER LOCALIZATION**

BY
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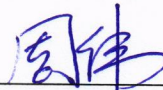
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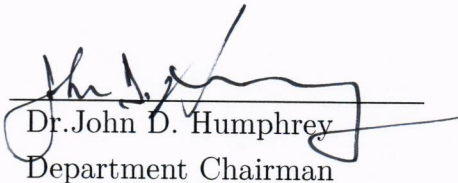
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I would like to dedicate my thesis to my family, who have played an important role in my academic journey. I am particularly grateful to my parents for their constant support, encouragement, and motivation which has pushed me to persevere. Additionally, I want to express my appreciation to my sister, who has been a constant source of support and encouragement throughout this journey.

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THESIS ABSTRACT

NAME: Kanan Suleymanli

TITLE OF STUDY: Scientific machine learning for microseismic hypocenter localization

MAJOR FIELD: GEOPHYSICS

DATE OF DEGREE: May 2023

Seismology regards earthquake localization as one of its most significant and challenging tasks. The seismic event’s location, focus point, or hypocenter is a crucial prerequisite for studying the event’s seismic activation. The first-arrival travel time inversion of the observed waves on the surface defines the event location. Though several methods have been developed to address this problem, they face limitations in computation and physics. This thesis proposes a data-driven approach to localize hypocenters using Fourier Neural Operators (FNOs) for real-time microseismic event localization. The proposed method aims to build a resolution-invariant model that can be quickly evaluated with one forward pass instead of retraining. The thesis initially trains a 2D FNO model to solve the eikonal equation and tests its approach on simple and complex velocity models like the Marmousi model. It successfully achieves high

accuracy in detecting the event location, even under extreme conditions such as missing receivers and high-level noise injection. Finally, the proposed method is applied to field data from Utah FORGE, and the results indicate its potential in practical seismic applications.

ملخص الرسالة

الاسم: اسم الطالب
عنوان الدراسة: عنوان الرسالة
التخصص: قسم الطلاب
تاريخ الدرجة العلمية: أدخل الشهر والسنة

عند كتابة ملخص ، ضع في اعتبارك مجرد ملخص هو ملخص وصفي قصير لأطروحتك. قد يختلف عدد الكلمات المقبولة على سبيل المثال: 200 – 250 يعتبر علم الزلازل توطين الزلازل أحد أهم المهام وأكثرها تحديًا. يعد موقع الحدث الزلزالي أو نقطة التركيز أو مركز الانفجار شرطًا أساسيًا أساسيًا لدراسة التنشيط الزلزالي للحدث. يحدد انعكاس وقت السفر عند الوصول الأول للموجات المرصودة على السطح موقع الحدث. على الرغم من تطوير العديد من الطرق لمعالجة هذه المشكلة ، إلا أنها تواجه قيودًا في الحساب والفيزياء. تقترح هذه الأطروحة نهجًا قائمًا على البيانات لتوطين الأشخاص الذين يعانون من نقص التركيز باستخدام عوامل Fourier العصبية (FNOs) من أجل توطين الأحداث الدقيقة في الوقت الحقيقي. تهدف الطريقة المقترحة إلى بناء نموذج ثابت للقرار يمكن تقييمه بسرعة بتمريرة أمامية واحدة بدلاً من إعادة التدريب. تقوم الأطروحة في البداية بتدريب نموذج FNO 2D لحل المعادلة eikonal واختبار نهجها على نماذج السرعة البسيطة والمعقدة مثل نموذج Marmousi. يحقق بنجاح دقة عالية في اكتشاف موقع الحدث ، حتى في ظل الظروف القاسية مثل المستقبلات المفقودة وحقن الضوضاء عالية المستوى. أخيرًا ، يتم تطبيق الطريقة المقترحة على البيانات الميدانية من FORGE Utah ، وتشير النتائج إلى إمكاناتها في التطبيقات الزلزالية العملية.

CHAPTER 1

INTRODUCTION

Microseismics is a field of study that involves analyzing small-scale seismic events generated by natural or artificial sources. Although too small to be felt by humans, these events can be detected and analyzed using sensitive seismometers, making microseismic monitoring a valuable tool for understanding the Earth's subsurface behavior and the effects of human activities on the environment. Applications of microseismic monitoring are varied, ranging from oil and gas exploration and production to earthquake monitoring and carbon sequestration. Additionally, the localization of earthquakes plays a critical role in seismic monitoring systems, with precise detection leading to better event monitoring and faster risk assessment, particularly in the case of anthropogenic or induced seismicity resulting from CO₂ storage, mining excavation, geothermal extraction, and hydraulic fracturing, which are generally classified as low-magnitude earthquakes or microseismic events.

The Traffic light system (TLS) is a method used to mitigate the risk of induced seismicity based on certain decision variables such as peak ground velocity and the event's magnitude [1]. The TLS is distinctive with its real-time capability of locating

events. Real-time location of low-magnitude seismic events are used for structural interpretation, optimize the extracted energy, and fault identification [2]. In the field of low-magnitude seismicity, automatic localization methods have been studied for more than a decade.

Over the years, various techniques have been proposed for localizing microseismic hypocenters. The traditional method involves using picked arrival times of P and S waves to estimate the unknown source location by minimizing the difference between observed and modeled [3] travel times. This method can provide absolute [4] or relative [5] locations based on different forms of the objective function. However, to overcome the limitations of travel-time-based methods, algorithms have been developed that directly utilize waveforms, avoiding the need for picking arrival times [6], [7], [8]. Despite their advantage of not requiring wave picking, waveform-based methods rely on precise knowledge of the velocity model to accurately model the waveforms. When the velocity model is not accurately known, these methods can result in larger errors. On the other hand, travel-time-based methods are less sensitive to velocity errors as averaging over velocities occurs when dealing with travel time

Researchers are taking advantage of the growing availability of data and computational resources to utilize machine learning algorithms for detecting, locating, and interpreting seismic events. Convolutional neural network-based models have been developed for source localization, using raw waveforms [9], [10], [11] or travel times [12], [13] as input. Even though these methods have been effective, they have a restricted ability to apply their knowledge beyond the data they have been trained on due to their dependence on training data statistics. In instances where historical data is not

accessible, like in microseismicity studies, researchers have turned to physics-informed neural networks (PINNs) [14] for source localization. One significant advantage of PINNs is that they do not need labeled training data, but rather include the underlying eikonal equation in the loss function throughout the training process. [15]. In addition, researchers have demonstrated that waveforms can be integrated into PINNs [16] to determine hypocenter locations by incorporating the wave equation into the loss function. The inclusion of physics in the model eliminates the need to generate large amounts of labeled data, enhancing the generalization capabilities of the algorithm beyond just supervised location methods. Nevertheless, the approach requires additional training for every new event or velocity variation, which restricts its feasibility for use in real-time monitoring systems.

Neural operators have recently surfaced as a viable technique for constructing surrogate models of physical systems, enabling simulations to be performed at nearly real-time speeds. Despite being a relatively new field, with only a few studies being published since 2019, neural operators show immense potential. However, they have only been employed in a limited number of computational science and engineering problems. Thus, their full potential has yet to be fully explored, especially in the realm of seismological applications.

Neural operators are a type of neural network that can learn to map complex relationships in classes of PDEs, making them powerful tools for building surrogate models that can represent a variety of conditions. The first major work in this area was DeepONet, introduced by Lu et al. [17], which included comprehensive error analysis. This approach has been applied to various problems, both through data-driven and

physics-informed optimizations [18], [19], [20], [21]. Recently, a variant was proposed that incorporates some features from classical finite element literature, as described in Patel et al. [22]. Other frameworks, such as Fourier Neural Operators (FNO) [23] and Graph Neural Operators (GNO) Li et al. [24], have also been explored. FNOs, in particular, have been widely studied and used for modeling two-dimensional wave propagation [25] and predicting high-frequency wavefields, based on a limited number of low-frequency components[26]. This study focuses on exploring the potential of FNOs for localizing microseismic events.

CHAPTER 2

THEORY

2.1 Fourier Neural Operators

Our proposed method for determining the location of a microseismic source involves using operator learning to solve the eikonal equation in a data-driven manner. Operator learning differs from conventional neural networks and allows for effective mapping between two function spaces. We implement this approach in the Fourier domain using Fourier neural operators (FNO), which allows us to obtain a travel time field over a specified computational domain. To demonstrate this approach, we use a 2D FNO model to solve the 2D eikonal equation, as depicted in Figure 2.1. Using FNOs offers several advantages, including reduced time complexity ($O(n^2)$), the ability to learn and generalize the partial differential equation (PDE) with the given data, and not requiring any boundary or initial conditions.

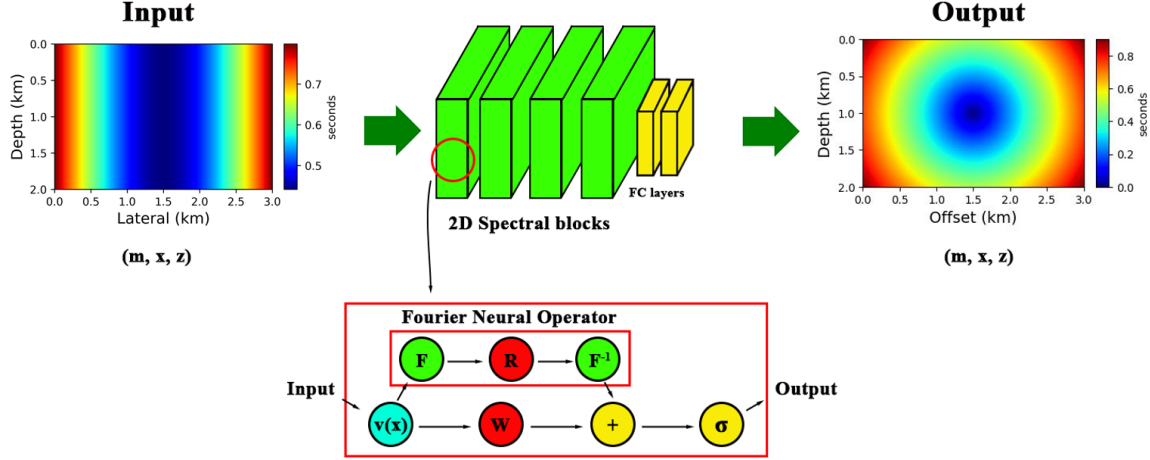


Figure 2.1: Schematic representation of 2D FNO model

2.1.1 Eikonal equation

The eikonal equation is a type of partial differential equation (PDE) that is used to explain how waves behave when they travel through a medium. The medium is represented by the domain Ω in d-dimensional space. This equation is of first-order and defines the travel time $T(x)$ needed for a wave to arrive at a specific point x from a point source, taking into account the velocity $v(x)$ of the wave in the medium at that point, and the gradient (∇) of the wave's phase function. The eikonal equation is crucial for determining the path that the wave follows as it travels through the medium, factoring in properties such as the medium's characteristics and the wave's velocity. Its general form is:

$$|\nabla T(x)|^2 = \frac{1}{v^2(x)}, \quad \forall x \in \Omega. \quad (2.1)$$

2.1.2 Data generation and training

In this study, the methodology begins with the assumption of having a surface array of receivers that record the initial arrival travel times for each event. These travel times serve as the input for the Fourier neural operator (FNO) model, while the output is the travel time across the entire domain. To generate input-output pairs, we select source locations within the domain and use them for training the FNO model. Notably, the FNO model requires that the input and output dimensions are identical. Therefore, we pad the grid points, excluding the receiver location, with the initial arrival travel times picked on the surface. This approach allows us to impose reasonable initialization for better generalization rather than using random initialization or padding with zeros.

Once the FNO model is trained, we can obtain the travel time field by inputting a given set of observed travel times. To determine the event location, we use the minimum value of the predicted travel time field, which yields the source's location. This approach provides an effective means of locating microseismic sources. 2.2.

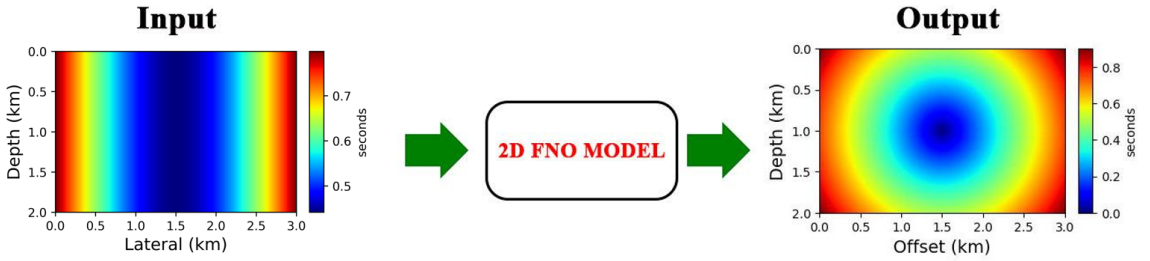


Figure 2.2: Workflow of training for the proposed method

Once the network is trained, we obtain the travel-time field of the given grid. To locate the event, we need to find the minimum value of the predicted travel time field. The coordinate of the minimum value is the event location that we are looking for.

CHAPTER 3

NUMERICAL EXAMPLES

To measure the feasibility of the idea, we conducted several experiments over two types of synthetic data.

3.1 Simple Velocity model

To evaluate the accuracy of our method in determining hypocenter locations, we conducted multiple tests. We started by using a $2 \times 3 \text{ km}^2$ vertically varying velocity model that we discretized into a grid of 101×151 points. An analytical method is used to calculate the genuine travel time map.

In the first test, we randomly selected 101 receivers on the model's surface to record the first arrival travel times. We then used 119 sources, distributed uniformly across the specified microseismic zone in the computational domain, for training. Following the training of the FNO model, we tested it on 50 randomly selected sources. Figure 3.1 shows the velocity model with a specified microseismic zone. The rectangular cyan box highlights the microseismic zone of interest, which spans 2 km on the x-axis, 0.75

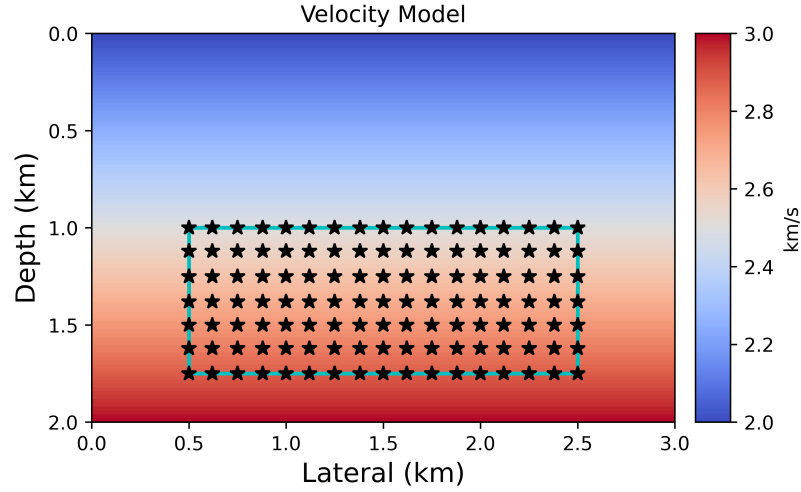


Figure 3.1: Vertically varying simple velocity model. The rectangular box shows the expected microseismic zone

km on the z-axis, and has a depth of 1 km. This is where we model the synthetic microseismicity. Figure 3.2 shows an absolute error histogram in source location coordinates. In Figure 3.3, the comparison between true and predicted synthetic event locations is depicted.

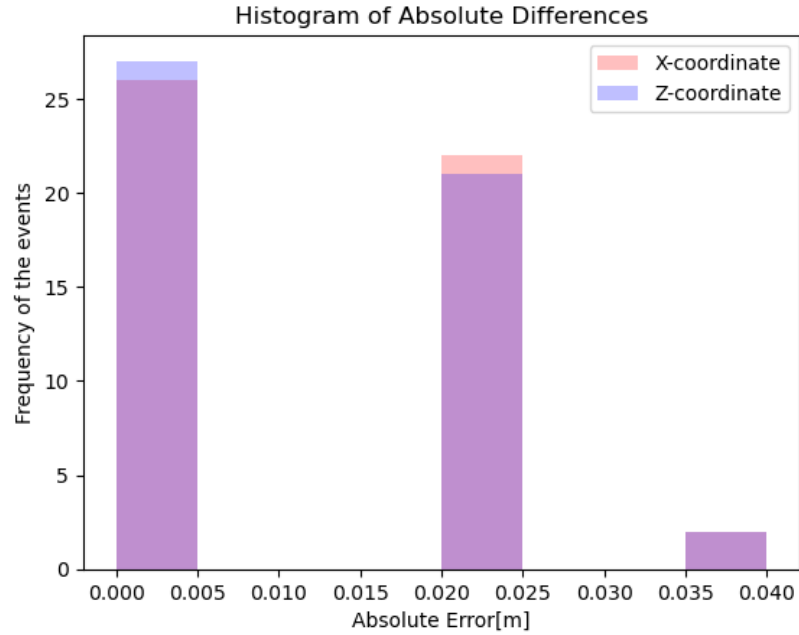


Figure 3.2: Simple velocity model: Absolute error in source locations

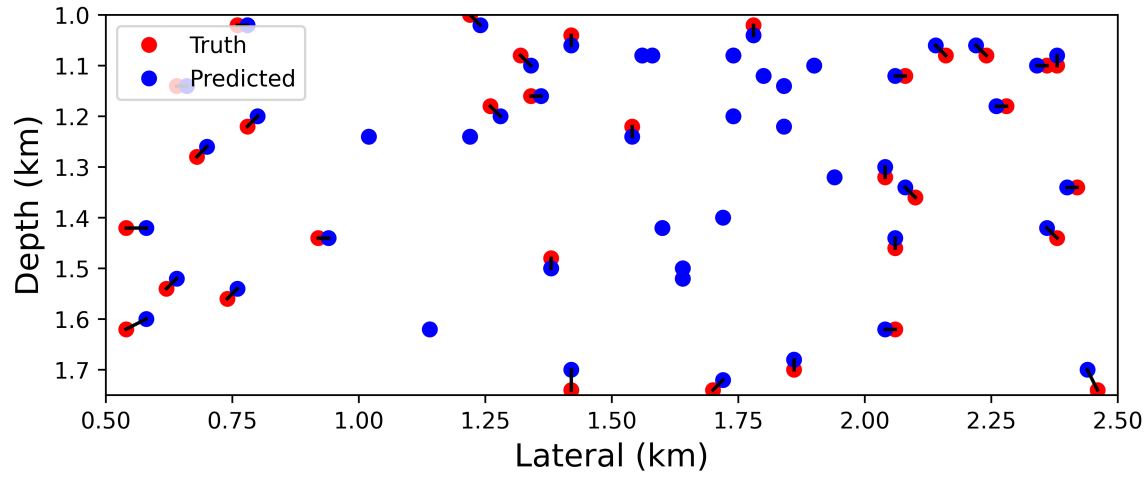


Figure 3.3: Simple Velocity model: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

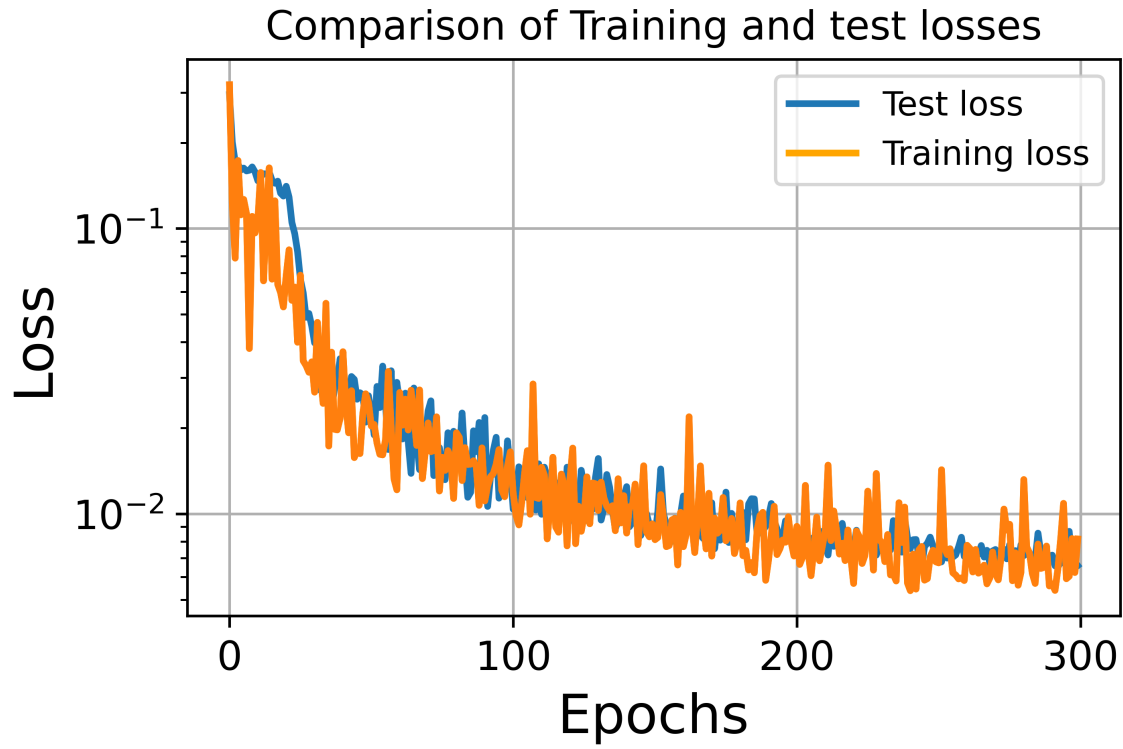


Figure 3.4: Simple Velocity model: Loss curve

3.1.1 Marmousi model

Next, we test the method on a more complex Marmousi [27] model. Marmousi is a synthetic model created using a geologic model sourced from the Cuanza basin located in Angola. It spans a total area of 9200 meters in the horizontal direction and a depth of 3000 meters with a grid size of 4 meters in both the horizontal and vertical directions. The model is discretized into 751x2301 grid points. To calculate the true travel-time map, we employed a fast marching algorithm sourced from the scikit-fmm package.[28]

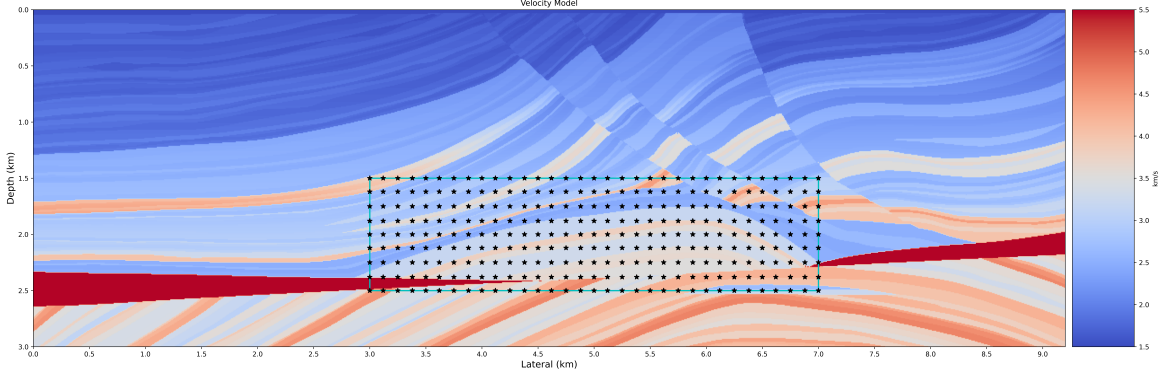


Figure 3.5: Marmousi velocity model: The rectangular box shows the expected microseismic zone

To begin with, we followed the same steps as a vertically varying simple velocity model. We selected 2701 receivers on the model surface to record the first arrival times, and we experimented with 297 source points uniformly distributed within the targeted microseismic area. Lastly, we evaluated the accuracy of our model by testing it on 50 sources chosen at random. The velocity model is depicted in Figure 3.5, with a specific zone of interest for microseismic activity, spanning 4 kilometers along the x-axis, 1 kilometer along the z-axis, and a depth of 1.5 kilometers. In Figure 3.6, an absolute

error histogram is presented for the source location coordinates. The performance of the synthetic event location prediction is evaluated in Figure 3.7, where a comparison between the predicted and actual locations is showcased.

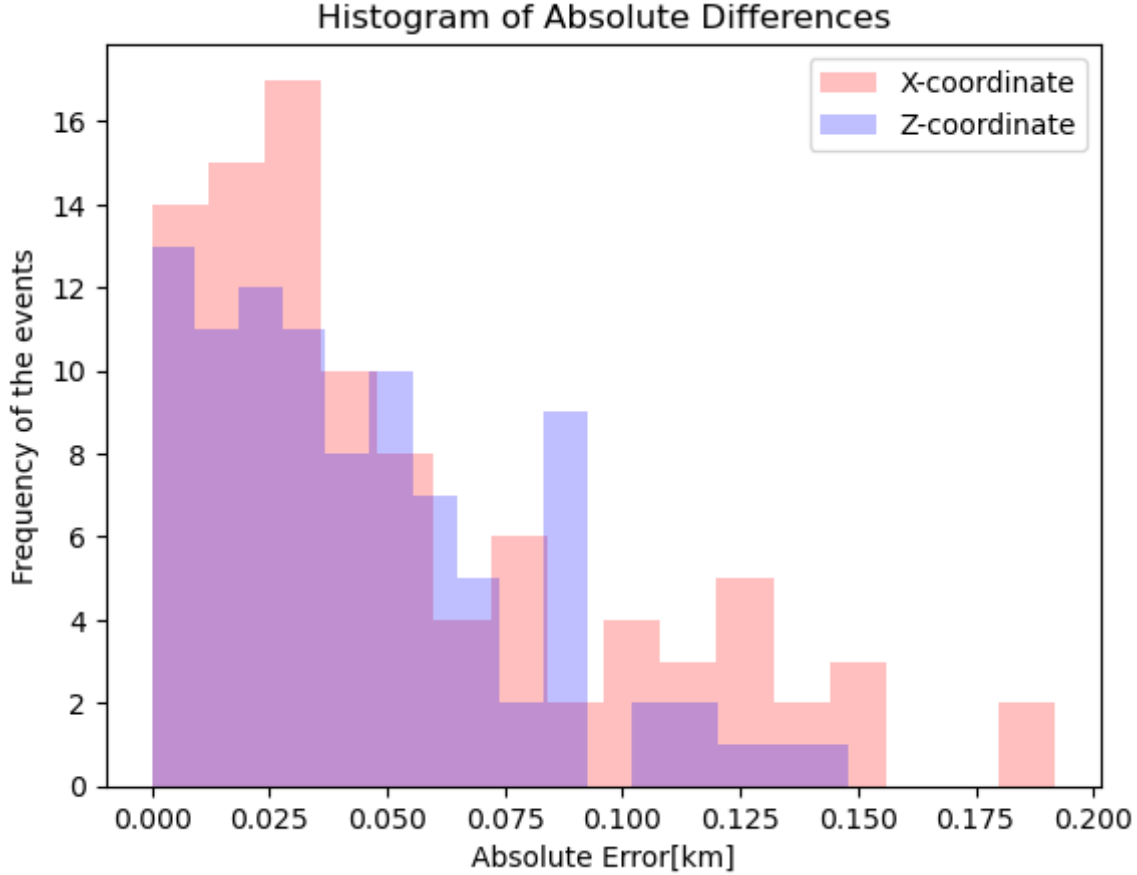


Figure 3.6: Marmousi velocity model: Absolute error in source locations

3.1.2 Marmousi model with missing receivers

To replicate practical scenarios, we continue the experiment with the random elimination of 30%, 40%, and 50%, of the receiver data. It is noteworthy that FNO imposes a requirement that the dimensions of its input and output must match. Consequently, with the elimination of a proportion of the receiver data, the input shape is corre-

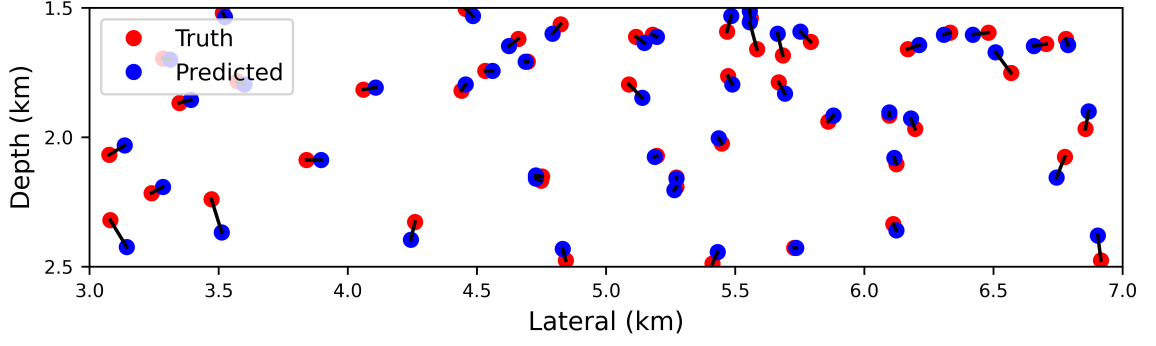


Figure 3.7: Marmousi model: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

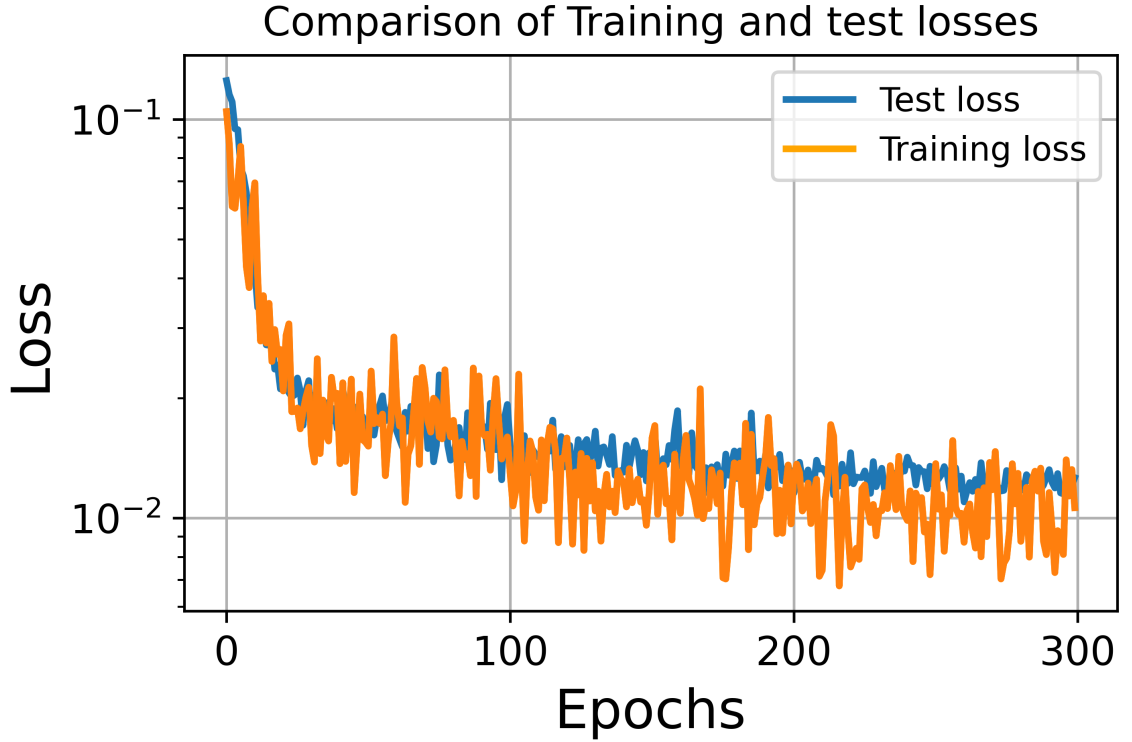


Figure 3.8: Marmousi Velocity model: Loss curve

spondingly altered. To resolve this limitation, we implemented a feed-forward neural network to interpolate and extrapolate the missing values, thereby restoring the initial input shape necessary for training the FNO model. We developed a four-layer feed-forward artificial neural network consisting of 60 nodes in each layer for predicting

the travel time corresponding to the position of each receiver after removal. Initially, we provided the network with the positions of the remaining receivers as input. Once the model was trained, we leveraged its predictive capability to estimate the missing receiver values. These values were then utilized as input for the FNO model. Figure 3.9 represents the neural network architecture, where the input node is the position of the receiver and the output node is the corresponding travel time for the given receiver. The impact of the removal rate on the FNO model's capacity to generalize is illustrated in Figure 3.10. This analysis aids in uncovering the model's capacity to handle missing data scenarios.

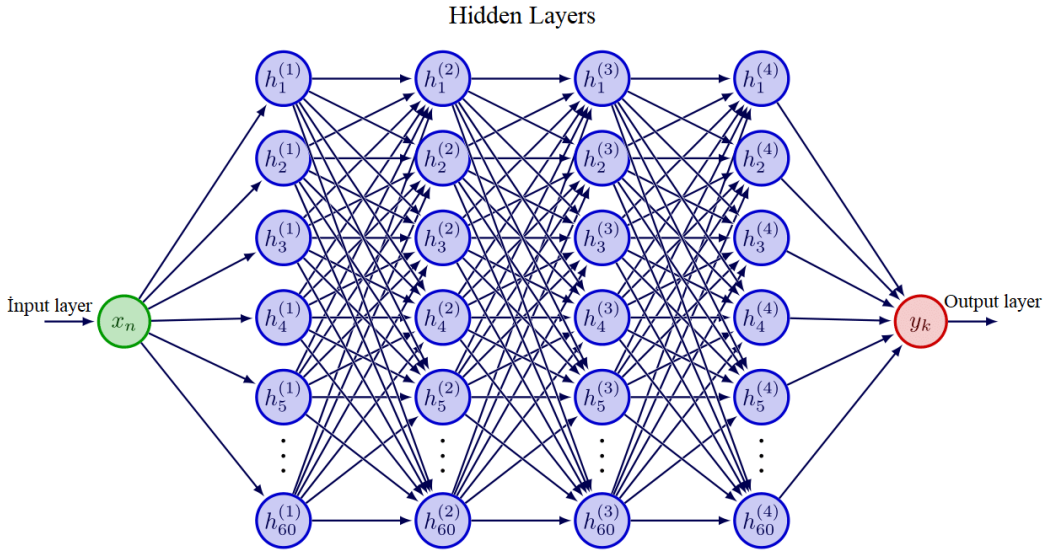


Figure 3.9: Architecture of the feed-forward artificial neural network used for predicting travel time. The input node represents the position of the receiver, and the output node indicates the corresponding travel time for the given receiver. The network has four layers, each consisting of 60 nodes.

To mitigate overfitting, we have established a fixed number of epochs for each removal rate. As the input size diminishes from 30% to 50% removal rate, the number of epochs must be correspondingly decreased to preserve the balance between bias

and variance. Table 3.1 shows how did we established the relationship between the removal rate and the number of epochs.

Table 3.1: Epochs per Removal Rate

Removal rate	Number of epochs
30%	150
40%	130
50%	110

30% Removal Rate

Initially, we conducted experiments by removing 30% of the receiver data and plotted the histograms of absolute errors in both the vertical and horizontal directions, as demonstrated in Figure 3.11. Upon comparison with Figure 3.6, it is observed that the precision of the location coordinates was only slightly degraded. With respect to the figure depicted in (3.12), which displays the comparison of predicted and actual locations, a comparable pattern was observed when compared with Figure 3.7.

40% Removal Rate

Subsequently, we conducted a test by removing 40% of the input data. The histograms of the absolute errors in the X and Z coordinates are presented in Figure 3.13. Furthermore, the performance of the FNO model in predicting the location of the synthetic events is demonstrated in Figure 3.14. It can be observed that the accuracy of the FNO model has degraded reasonably as compared to the test with 30% removal.

50% Removal Rate

Finally, we conducted an experiment in which half of the receiver data was removed, and the missing data was interpolated using a feed-forward neural network. The resulting input was fed into the FNO model to estimate the source location. The absolute errors in source locations for this case are shown in Figure 3.15, and the location comparison is demonstrated in Figure 3.16. While comparing the results to those obtained from the 40% removal rate, we observe a significant degradation in performance due to the increased proportion of missing receiver data. However, the results are still sufficiently accurate for the FNO model to build the travel-time map and enable precise event localization, despite the extreme rate of missing receiver data.

3.1.3 Marmousi model with noise injection and missing receivers

Next, we continue the study with 30% removal rate. In continuation with the utilization of the Marmousi velocity model, the study proceeds to evaluate the precision of location determination by introducing three levels of noise (high, medium, and low) to the travel-time observations. Employing a comparable experimental protocol to the previous test, we introduce noise with standard deviations of 0.2, 0.1, and 0.05 seconds to the travel-time observations. Figure 3.17 illustrates a comparison between the original travel-time observations and the modified observations with varying noise levels. The loss curve depicted in Figure 3.18 demonstrates the impact of injecting three distinct noise levels. Despite the introduction of high-level noise, the model's

generalization capability remains intact.

Effect of low-level noise

Building upon the previous experimental results, we conducted further investigations to evaluate the impact of noise on the system. Specifically, we utilized the dataset obtained from the model with a configuration with a significant portion of receiver data removed, more specifically 30% of the total data. Figure 3.19 illustrates the absolute error in source locations for the Marmousi model with a 30% removal rate and high-level noise. Additionally, Figure 3.20 depicts the comparison between the predicted locations generated by FNO (represented in blue) and the corresponding actual locations (represented in red) for the same Marmousi model configuration. These visualizations offer valuable insights into the behavior of the FNO model in the presence of noise and partial removal of receiver data.

Effect of mid-level noise

Following our investigation into the impact of low-level noise on the system, we extended our study to include mid-level noise. Using the data generated by the model with a 30% removal rate, we added noise with a standard deviation of 0.1 s to the travel time observations. Figure 3.21 displays the absolute error in source locations for the Marmousi model under this configuration, while Figure 3.22 shows the predicted and actual locations for the same data. These visualizations enable us to observe the FNO model's performance under a higher level of noise and further understand its behavior in the presence of incomplete receiver data.

Effect of high-level noise

To further investigate the impact of noise on the system, we conducted another experiment with high-level noise added to the Marmousi model with 30% removal rate. The purpose of this experiment was to evaluate the robustness of the FNO model under conditions of high noise and partial receiver data removal. Figure 3.23 displays the absolute error in source locations for this configuration. Meanwhile, Figure 3.24 presents the comparison between the predicted locations generated by FNO (shown in blue) and the corresponding actual locations (shown in red). These visualizations provide insights into the behavior of the FNO model under conditions of high noise and partial receiver data removal. By conducting these experiments, we were able to assess the performance of the FNO model in practical scenarios where noise and data loss are prevalent.

Our findings indicate that as the noise level increases, there is a slight decrease in the performance of the FNO model. However, the decrease is not significant, and the model still performs reasonably well even under high-level noise conditions. For instance, in the case of the Marmousi model with high-level noise and 30% receiver data removal, the maximum deviation on the Z axis is just 200 meters approximately 0.07 km, which is only slightly higher than the corresponding error in the noise-free case. These results suggest that the FNO model is robust to noise and can still provide accurate predictions even when the input data is noisy.

3.1.4 Real Data

Microseismic monitoring plays a crucial role in geothermal sites as it allows for the detection and characterization of induced seismicity, providing valuable insights into reservoir behavior and hydraulic fracturing operations. Hence, in our investigation, we utilized the Utah FORGE Dataset, a compilation of geologic and geophysical data from the Utah FORGE site, to apply the FNO model to real data. This dataset comprises a diverse range of data types, such as borehole data, seismic data, gravity data, and geologic maps, enabling a comprehensive analysis of microseismic events and their localization using scientific machine learning techniques.

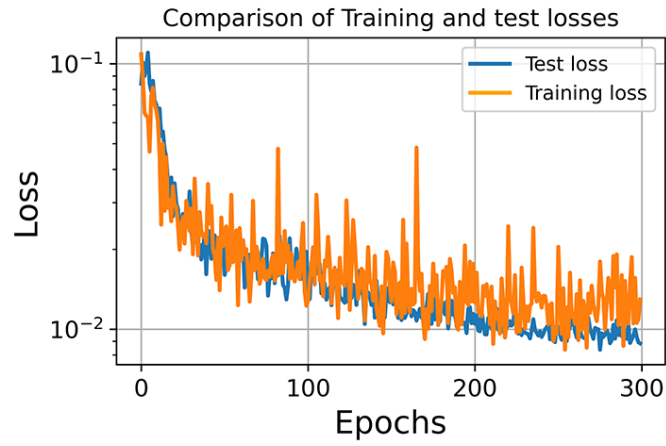
The Utah Frontier Observatory for Research in Geothermal Energy (FORGE) is a research facility that aims to facilitate the development of commercial enhanced geothermal energy (EGS). Located in south-central Utah, the facility consists of various components. The crystalline basement reservoir, predominantly made up of granitoid, has temperatures reaching around 200°C. Currently, the facility includes the first of two horizontally deviated wells, named 16A(78)-32, which is 8,500 feet deep. Additionally, there are three boreholes—58-32, 78B-32, and 56-32—each with depths exceeding 7,500 feet, available for seismic monitoring. Another borehole, 78-32, around 3,500 feet deep, is instrumented with Distributed Acoustic Sensing (DAS) equipment throughout its depth. Note that 78B-32 also has usable DAS equipment to approximately 3,500 feet. [29]

For our research, we will employ the sonic log data acquired from well 58-32 (as depicted in Figure 3.26) to construct a 2D model (as shown in Figure 3.27) by means

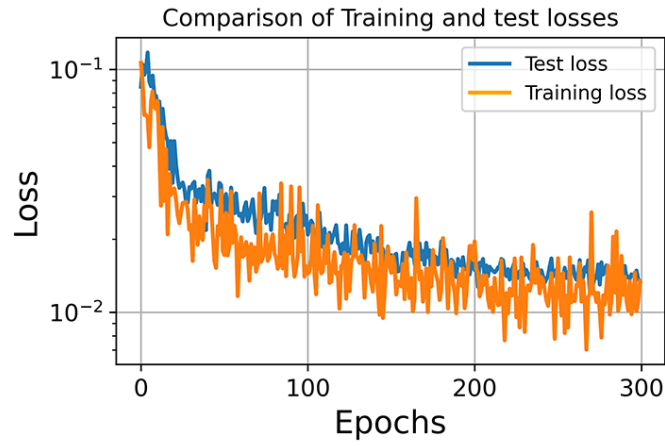
of interpolating the sonic log. Furthermore, we will integrate the recorded picks from well 78-32 as a component of our analysis.

The input data for our study consisted of vertically positioned Distributed Acoustic Sensing (DAS) receivers obtained from well 78-32. The challenging nature of the problem arises from the limited velocity model resulting from the sonic log measurement (which begins at a depth of 656 meters) and the restricted coverage of DAS measurements within a specific area.

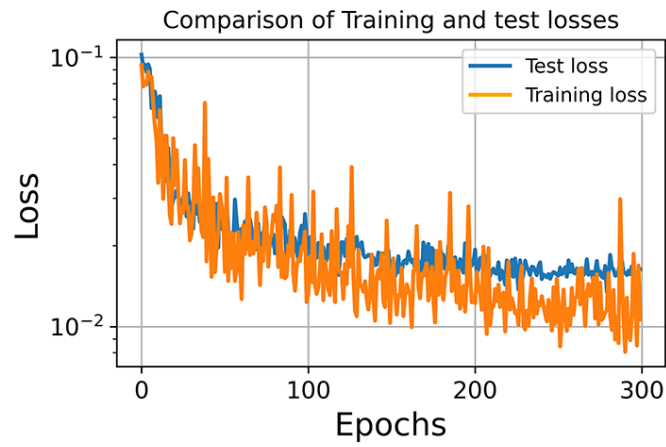
Despite the presence of various limitations, the model continues to exhibit the critical capability of generalization, which holds significant importance in real-life applications, particularly in real-time event localization. The loss curve of the model training is illustrated in Figure 3.28. The training data is generated in accordance with the real Distributed Acoustic Sensing (DAS) picks, which are only available within a limited range. In order to demonstrate the real-time capabilities of the trained FNO model for microseismic event monitoring, we conducted a final test to locate a single perforation shot. Figure 3.29 displays the corresponding coordinates of both the prediction and the ground truth for the perforation shot.



A)



B)



C)

Figure 3.10: Loss curves for the three cases of missing receivers: 30% (a) , 40% (b), and 50% (c)

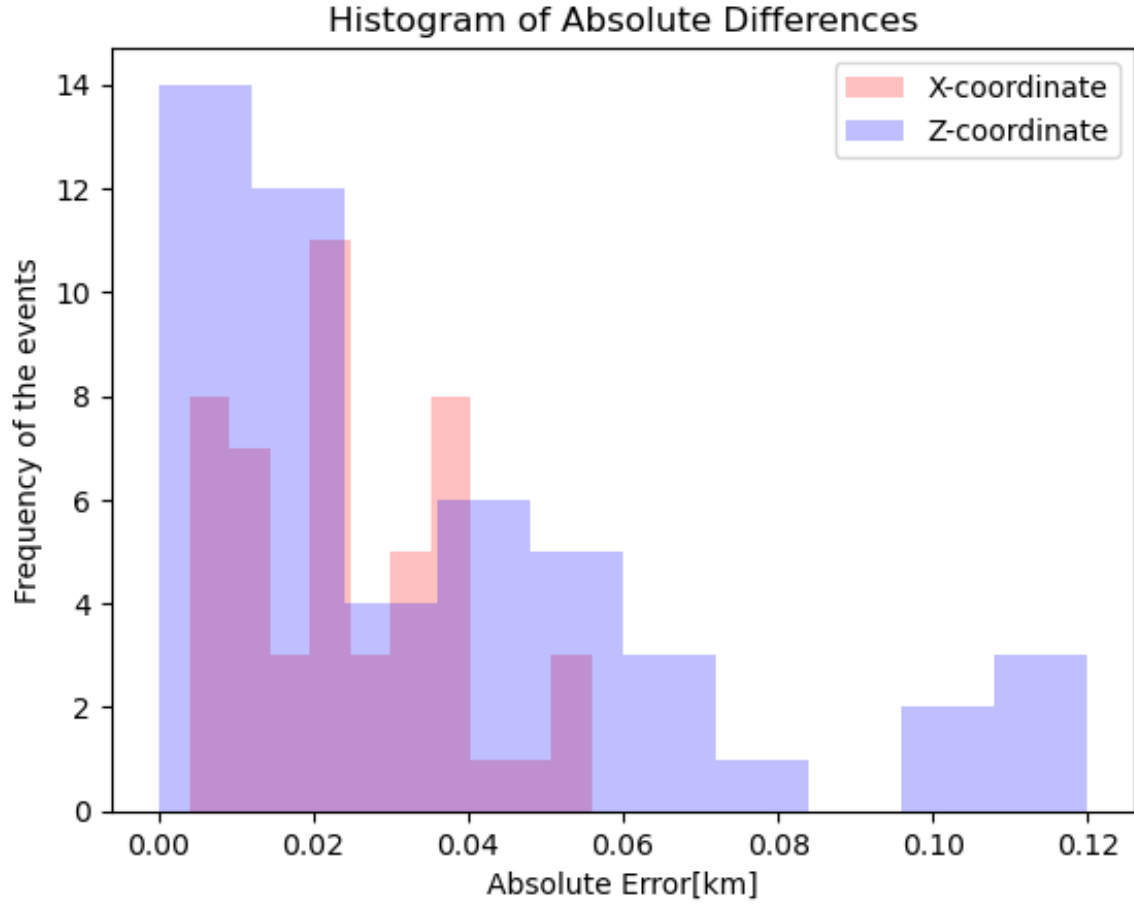


Figure 3.11: Marmousi model with 30% removal rate: Absolute error in source locations

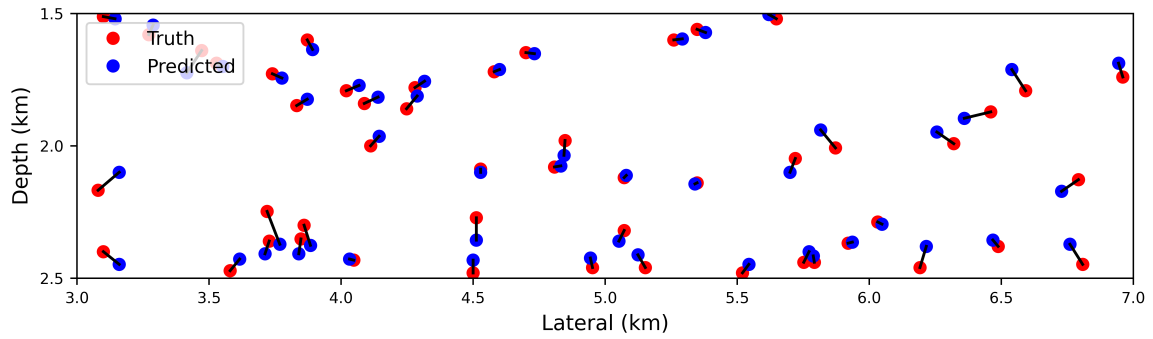


Figure 3.12: Marmousi model with 30% removal rate: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

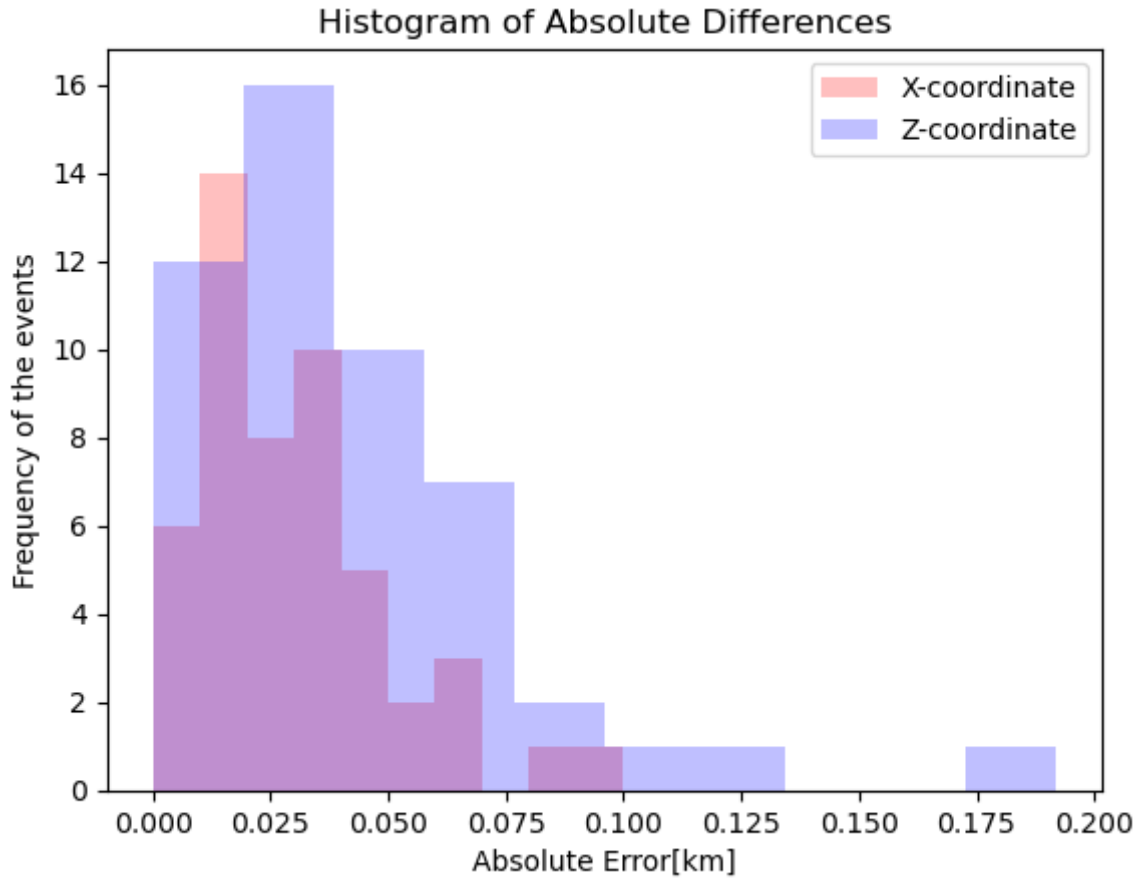


Figure 3.13: Marmousi model with 40% removal rate: Absolute error in source locations

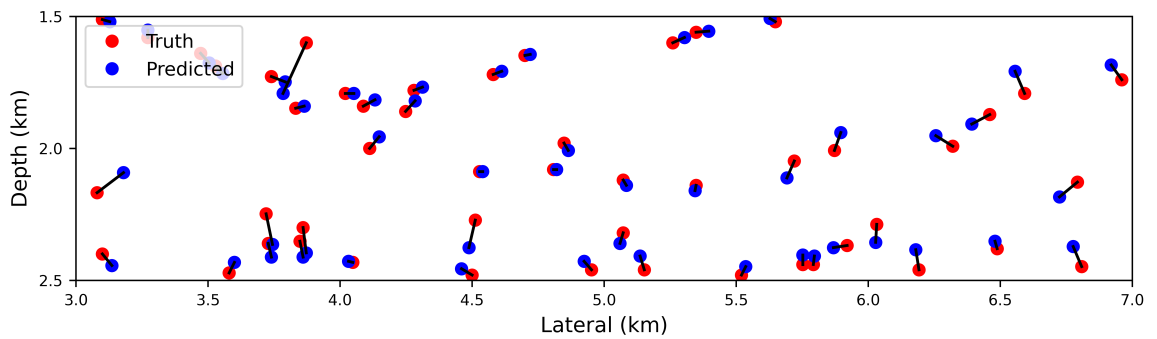


Figure 3.14: Marmousi model with 40% removal rate: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

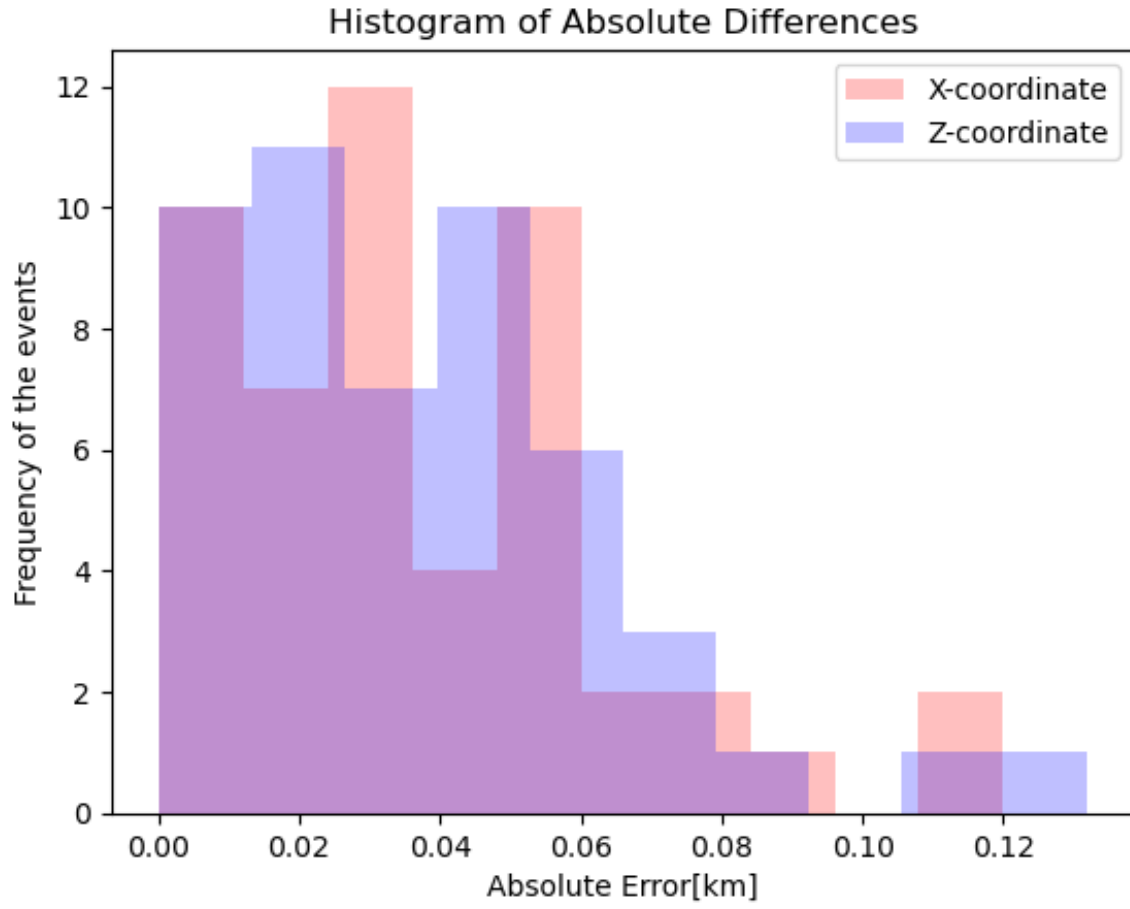


Figure 3.15: Marmousi model with 50% removal rate: Absolute error in source locations

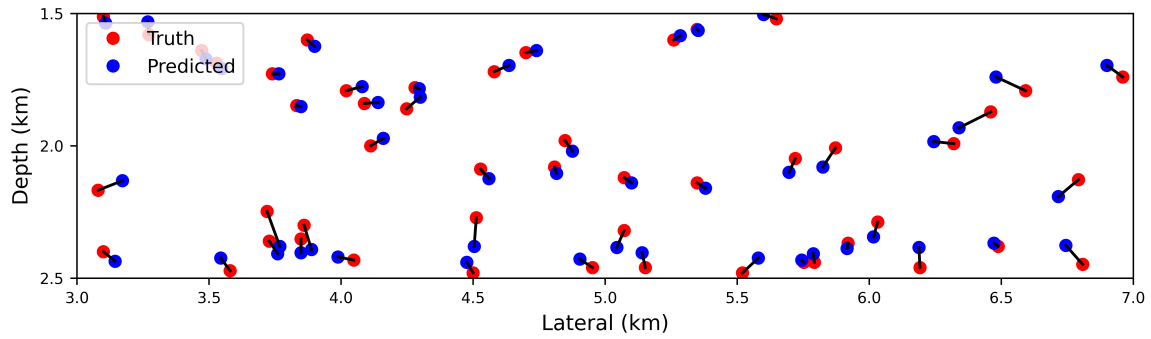


Figure 3.16: Marmousi model with 50% removal rate: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

Comparison of Noisy Signals with Normal Signal

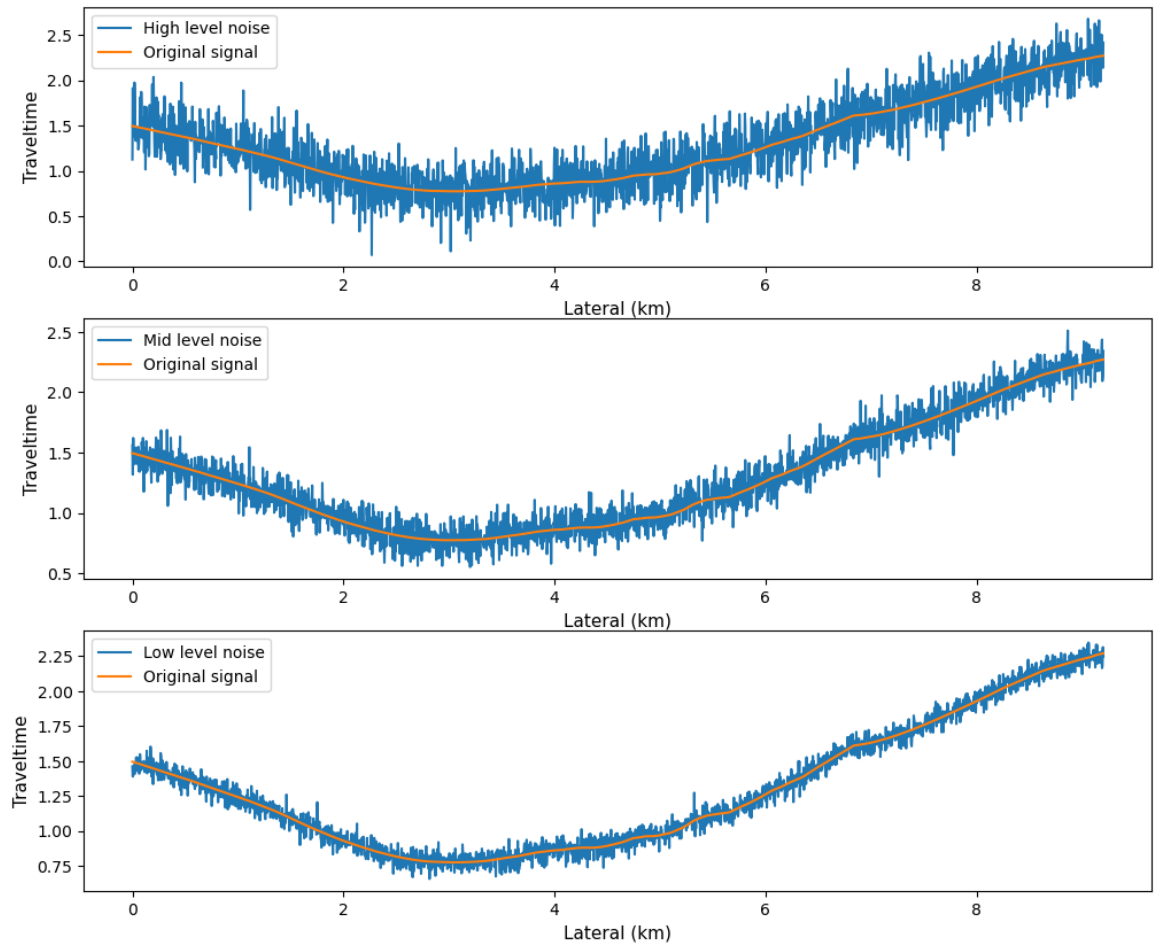
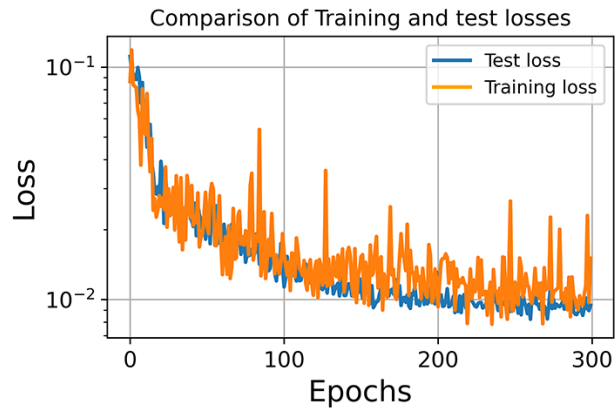
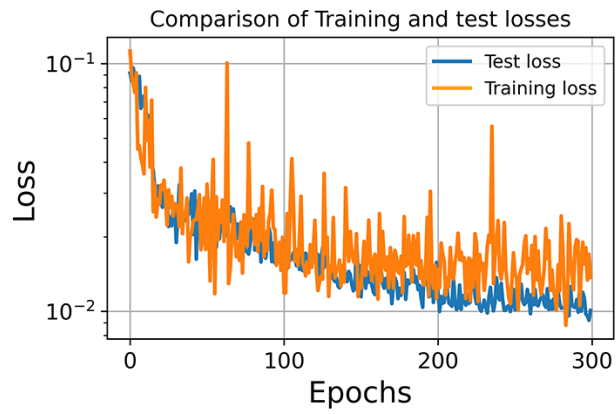


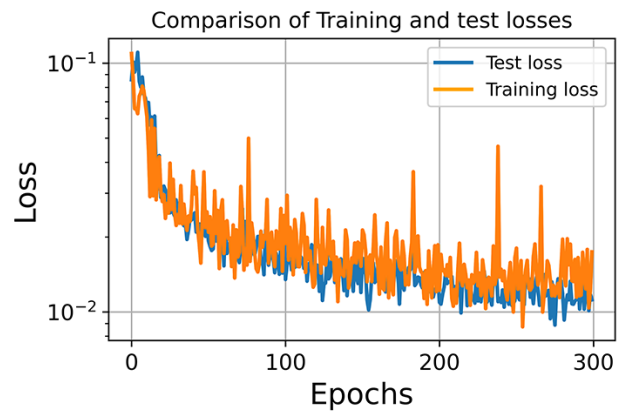
Figure 3.17: Comparison of travel-time observations with varying levels of added noise, illustrating the impact on location accuracy for the Marmousi velocity mode



A)



B)



C)

Figure 3.18: Loss curves for the three-level of noise 30% missing removal rate: Low (a), Mid (b), and High (c)

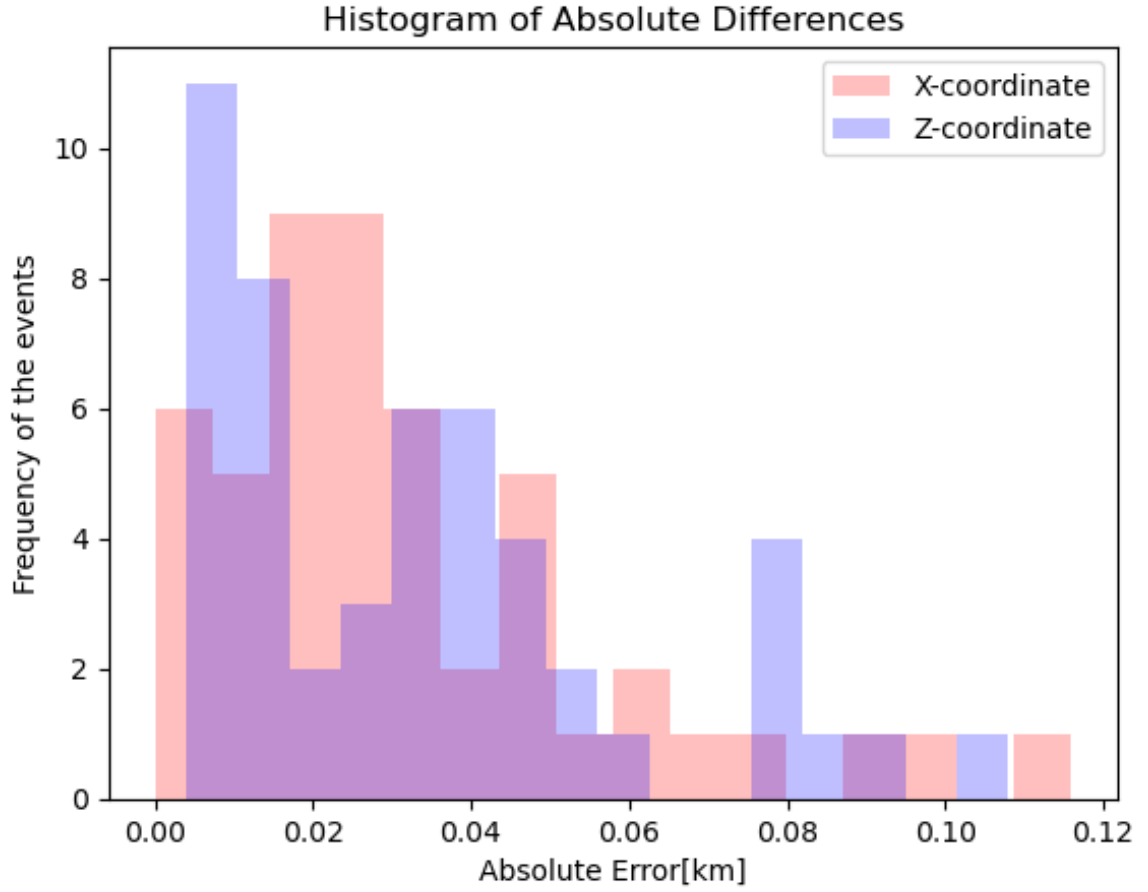


Figure 3.19: Marmousi model with 30% removal rate + low-level noise: Absolute error in source locations

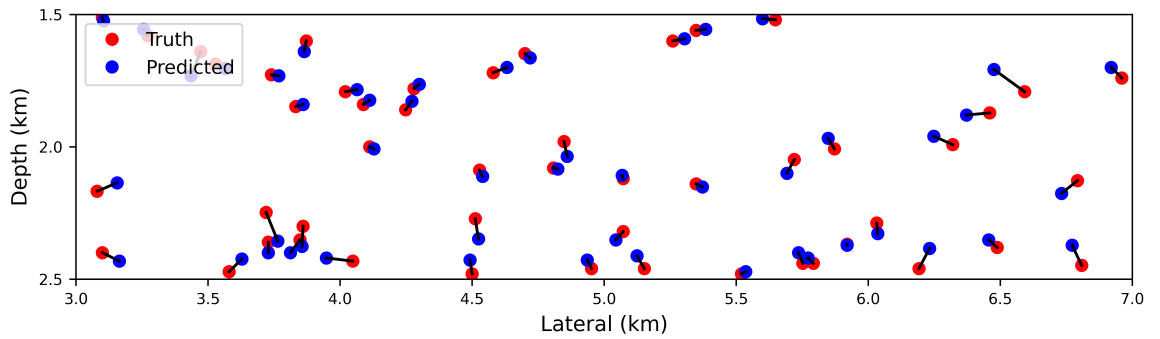


Figure 3.20: Marmousi model with 30% removal rate + low-level noise: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

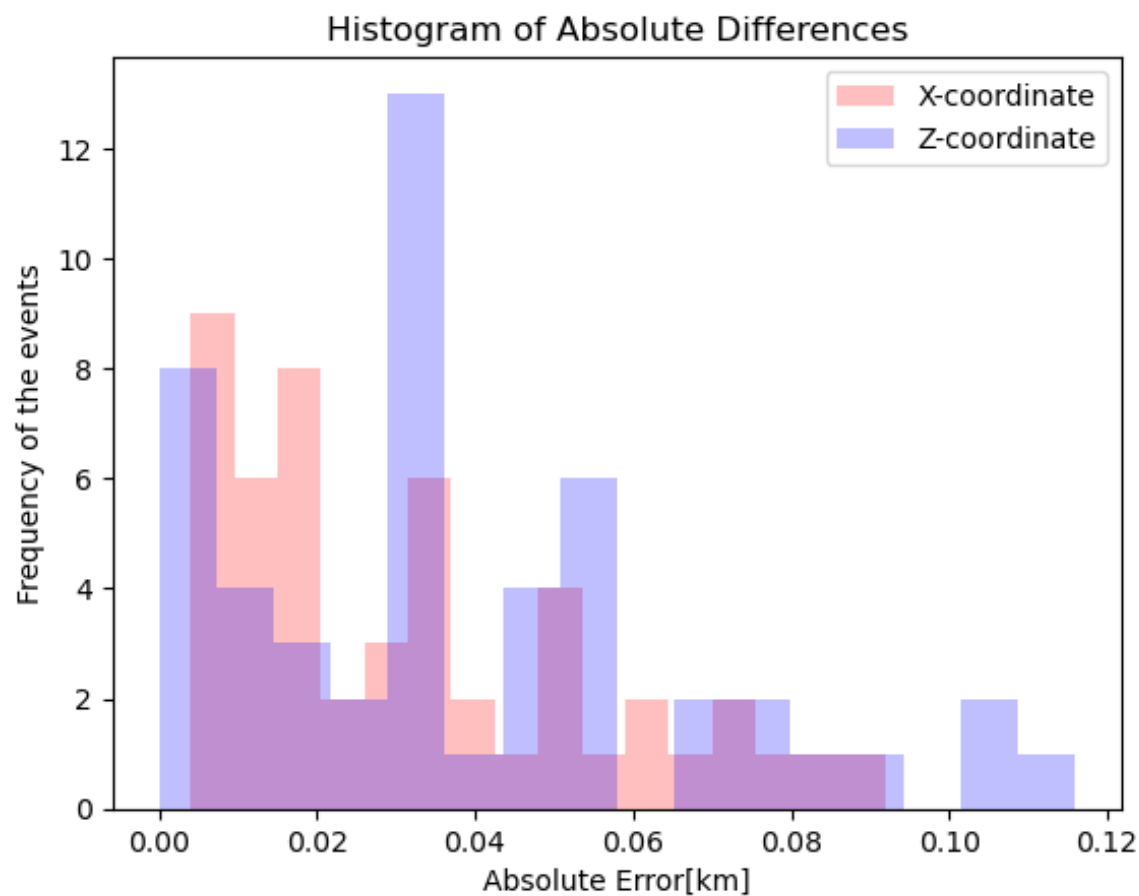


Figure 3.21: Marmousi model with 30% removal rate + mid-level noise: Absolute error in source locations

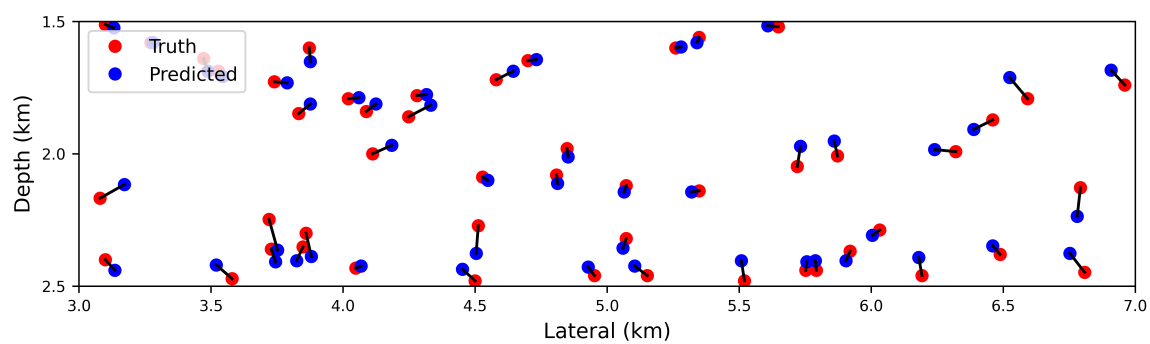


Figure 3.22: Marmousi model with 30% removal rate + mid-level noise: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

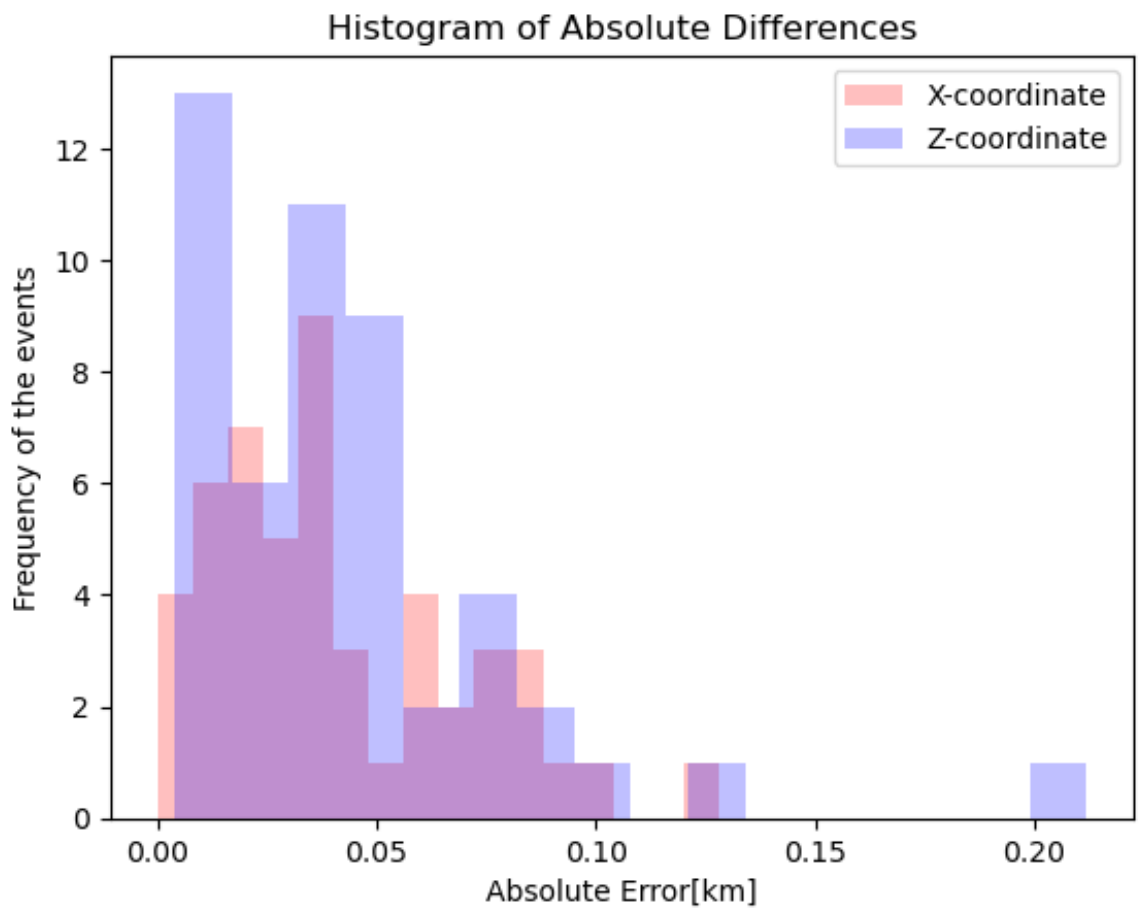


Figure 3.23: Marmousi model with 30% removal rate + high-level noise: Absolute error in source locations

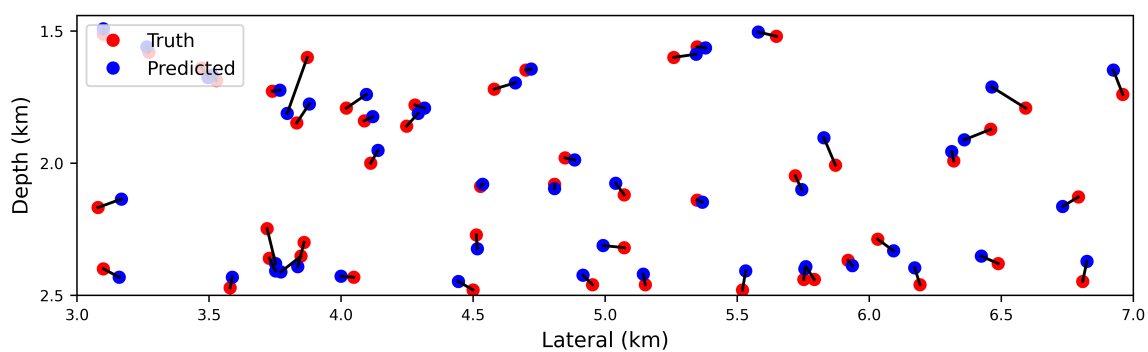


Figure 3.24: Marmousi model with 30% removal rate + high-level noise: The comparison of predicted locations (shown in blue) generated by FNO with the corresponding actual locations (shown in red).

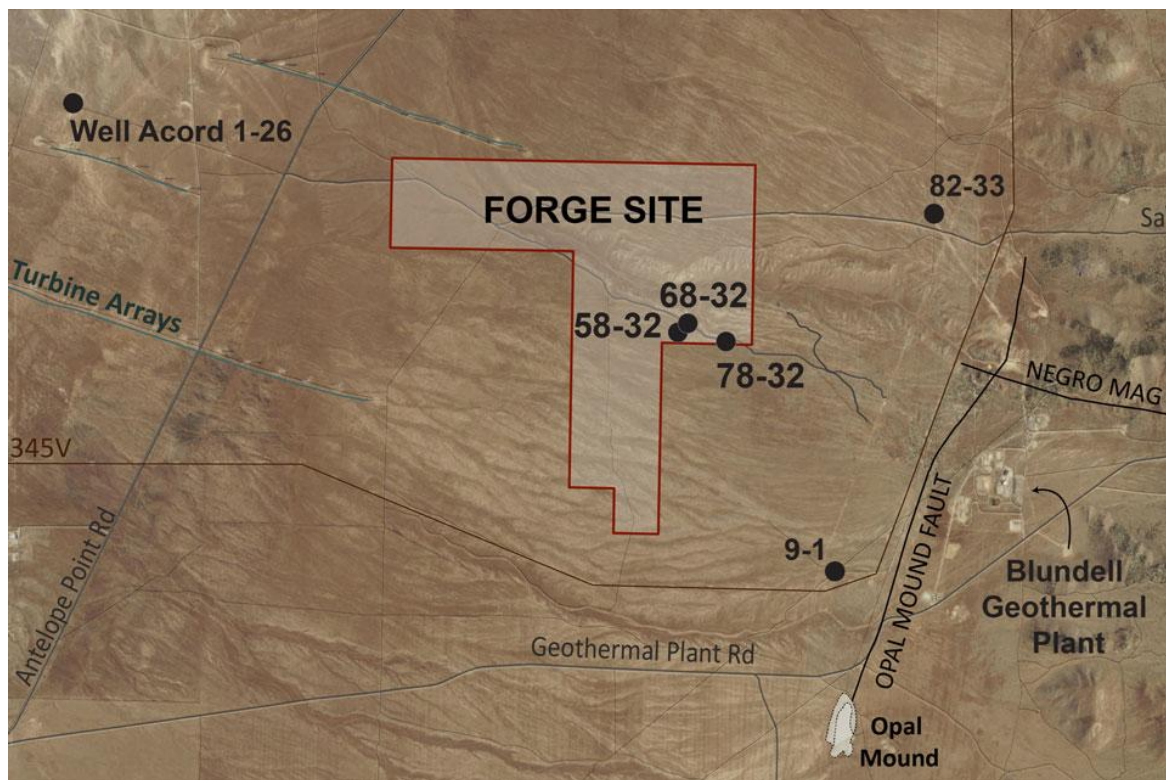


Figure 3.25: Forge site

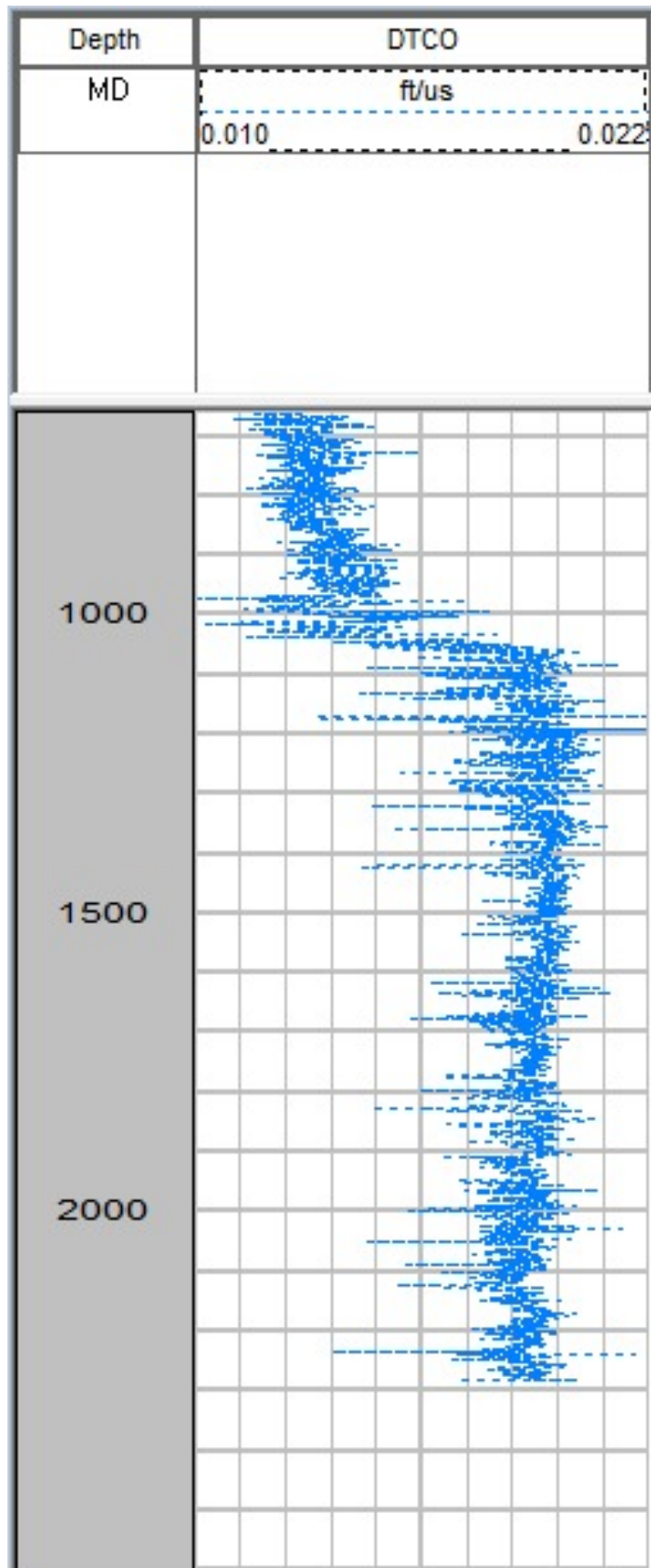


Figure 3.26: The sonic log recorded on well 58-32

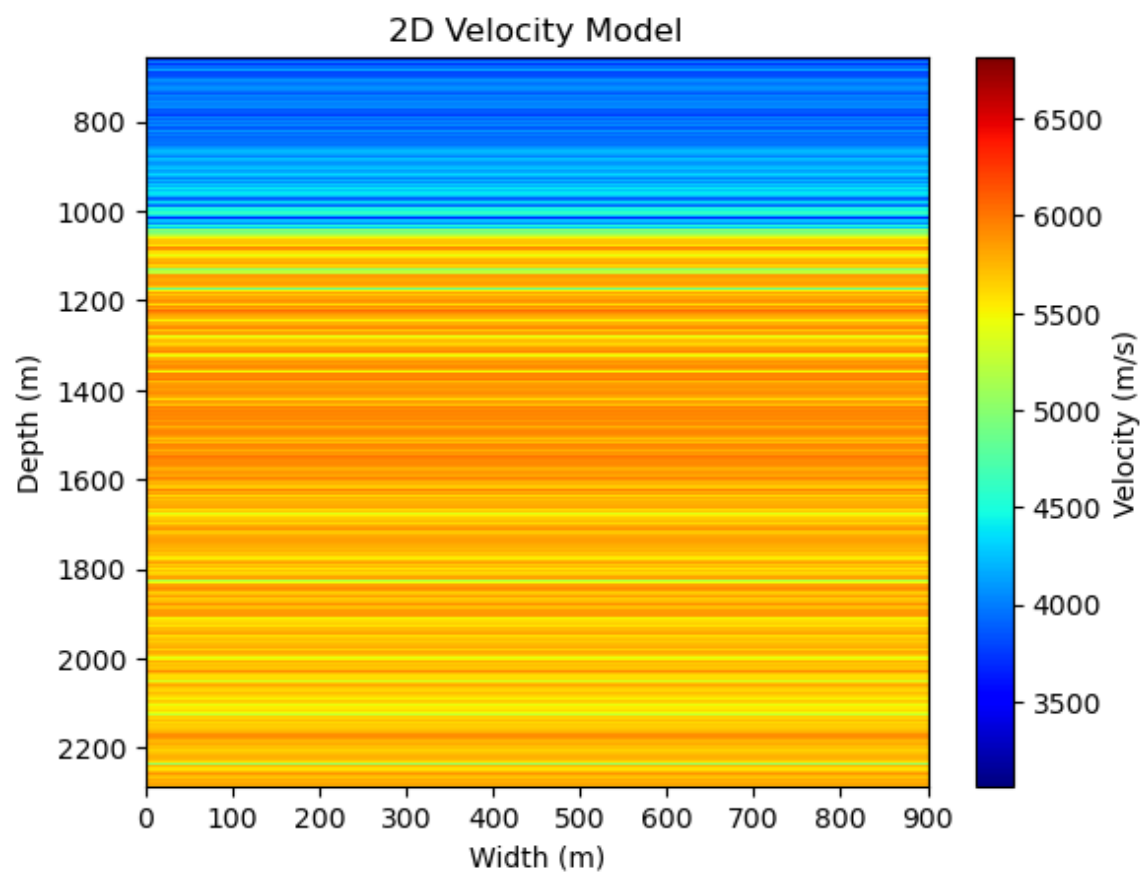


Figure 3.27: 2D velocity model using extrapolation of sonic log

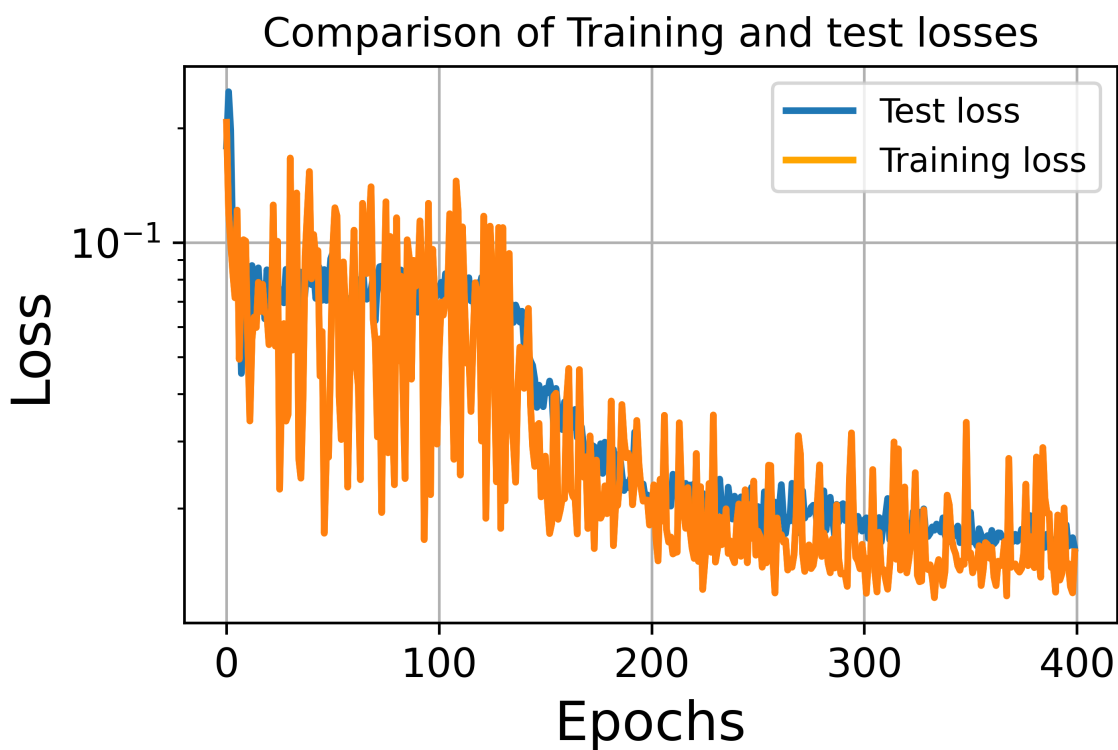


Figure 3.28: Loss curve for the training of FORGE data

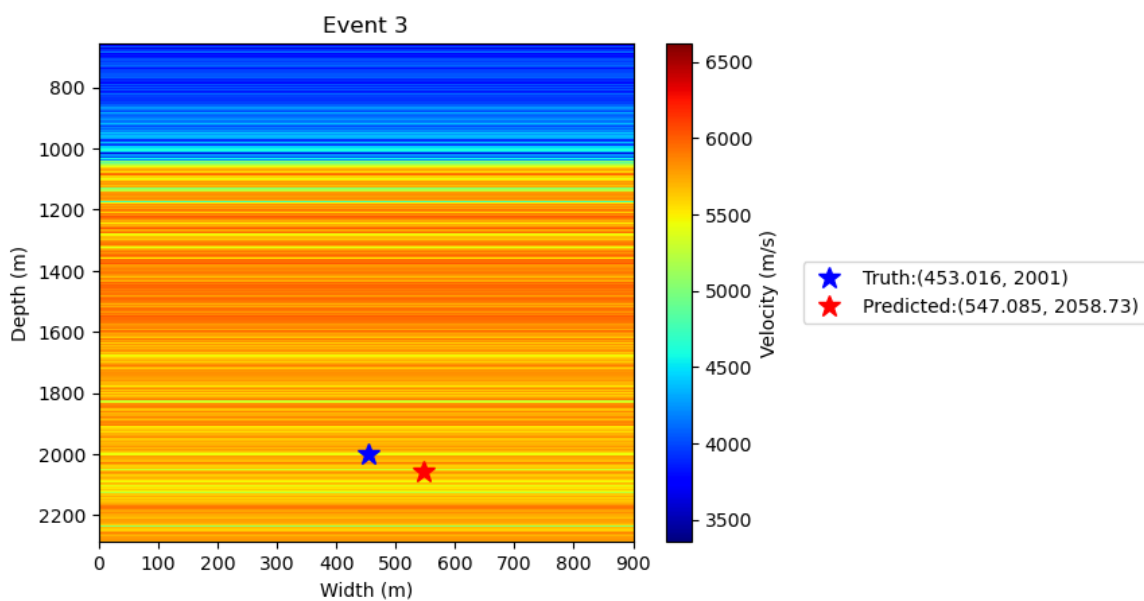


Figure 3.29: Actual and predicted location on velocity model

CHAPTER 4

CONCLUSION

4.1 Conclusion

In conclusion, the development of an FNO-based framework for hypocenter localization marks a significant advancement in microseismic analysis. The framework demonstrates robustness in handling noisy arrival times and missing picks, with the interesting observation that injecting a certain level of noise can even enhance the results in synthetic data. The successful testing of the model on real data from the FORGE site showcases its real-time event localization ability, overcoming data limitations. Moving forward, the application of this method to 3D models holds great potential for more comprehensive analysis. The utilization of 3D FNOs for velocity generalization can further enhance the robustness of microseismic applications. Additionally, the integration of physics-informed neural operators (PINO) offers promising avenues for future research and advancement in this field. Real-time event localization in microseismic monitoring is of paramount importance, providing valuable insights into reservoir behavior and hydraulic fracturing operations, ultimately optimizing the

safety and productivity of geothermal energy extraction processes.

APPENDIX A

PROOFS

APPENDIX B

SUPPLEMENTARY MATERIAL

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