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A MULTI-FIDELITY DEEP OPERATOR FRAMEWORK WITH GENERATIVE ADVERSARIAL NETWORK FOR LOAD PREDICTION AND DISPLACEMENT RECONSTRUCTION OF TUNNEL STRUCTURES

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Abstract: Accurately predicting external loads and evaluating the health condition of tunnel structures are fundamental for ensuring the safety and resilience of underground infrastructure. This study presents an advanced multi-fidelity Deep Operator Network (MF-DeepONet) framework that incorporates a generative adversarial network (GAN) to address these challenges by integrating simulation-based low-fidelity data and sparse high-fidelity real-world measurements. Within this framework, the GAN is employed for inverse prediction of external loads from measured displacements, ensuring that the resulting load distributions remain consistent with simulation-informed patterns. The predicted loads are then fed into the MF-DeepONet to reconstruct the full displacement field through data fusion. The MF-DeepONet framework consists of two subnetworks: a low-fidelity network trained on data generated by a validated macro-scale numerical model to capture general deformation patterns of tunnel linings, and a high-fidelity network trained on limited real-world monitoring data to learn the correlations between field observations and simulations. A full-scale test on a quasi-rectangular shield tunnel (QRST) lining structure is conducted for validation. The results demonstrate that the proposed framework enables both reliable estimation of external loads and accurate reconstruction of displacement fields, showing strong agreement with experimental observations. This data-driven approach significantly reduces reliance on dense sensing networks and offers a robust, interpretable solution for tunnel health diagnosis and predictive maintenance in real-world engineering applications.

Keywords: Tunnel lining, Multi-fidelity DeepONet framework, Generative adversarial network (GAN), Limited measurements, Inverse load determination, Health evaluation

1. INTRODUCTION

In tunnel engineering, accurately understanding the external loading conditions and their impact on the structural integrity of tunnel linings is of paramount importance (X. Huang et al., 2020; Xu et al., 2023). Tunnels, as critical components of urban infrastructure, are often subjected to complex and variable loading scenarios during both construction and service stages, including overburden pressure and groundwater variations (Colombo et al., 2018; Guo et al., 2018; J.-L. Zhang et al., 2023; W. Zhang et al., 2022). These loads, if not properly identified and evaluated, may induce progressive deformation, joint failures, or even catastrophic collapse (W. Lu et al., 2023; Qiu et al., 2021). Therefore, precise estimation of external loads and timely evaluation of the structural health condition are essential for ensuring the safety, durability, and operational continuity of tunnel systems (H. Huang et al., 2024; Soga et al., 2025).

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Conventional methods for tunnel health assessment typically rely on numerical simulations calibrated against a limited set of field measurements. While finite element (FE) modeling provides a powerful tool for analyzing tunnel responses under prescribed loads, the inverse identification of unknown external loads based on observed displacements remains a major challenge (Gao et al., 2025; Yuan et al., 2021). This is particularly true in complex tunnel geometries or segmental linings with discontinuities and nonlinear joint behaviors, where the system's response may be highly sensitive to localized loading (X. Liu et al., 2025; Z. Liu, B. T. Cao, et al., 2025; Z. Liu, X. Liu, et al., 2025). Furthermore, such inverse analyses often suffer from ill-posedness and high computational cost, limiting their practicality in real-time monitoring and decision-making scenarios. In parallel, dense deployment of sensors across the tunnel lining to directly capture external loads or reconstruct full displacement fields is rarely feasible in practice due to prohibitive installation and maintenance costs (Latif et al., 2023; Lin et al., 2023; X. Zhang et al., 2024). As a result, there is a growing need for data-driven frameworks that can effectively leverage sparse measurements, integrate prior knowledge from simulations, and provide reliable predictions of both loading conditions and structural states.

With the rapid development of physics-informed machine learning, especially the operator learning technology (Koric et al., 2024; L. Lu et al., 2021), new opportunities have emerged to overcome these challenges. By treating external loads and structural responses as functional inputs and outputs, operator learning-based models such as DeepONet enable direct mappings between them, bypassing traditional physics-based formulations and offering significant advantages in terms of flexibility, efficiency, and generalizability (Koric et al., 2024; L. Lu et al., 2021).

Several recent studies have demonstrated the effectiveness of Deep Operator Networks (DeepONet) in solving complex forward and inverse problems in engineering mechanics. He et al. (2023) introduced a ResUNet-based DeepONet for elastoplastic stress field prediction, significantly reducing computational cost. Garg et al. (2022) employed DeepONet for time-dependent reliability analysis under stochastic loads, showcasing its capability in uncertainty quantification and zero-shot learning. Ahmed et al. (2025) proposed a physics-informed DeepONet with stiffness-based loss terms to improve accuracy in displacement prediction under static loads. Koric et al. (2024) further extended DeepONet to small-strain plasticity problems involving variable material properties and loading conditions. These advances demonstrate DeepONet's promise as a flexible and efficient surrogate model for both forward simulation and inverse estimation tasks.

Building on these developments, Chen Xu et al. (2024) proposed a multi-fidelity DeepONet (MF-DeepONet) framework that integrates simulations with sparse real-world measurements to reconstruct displacement fields induced by tunnel boring machine (TBM) excavation in real-time. In a follow-up study (C Xu et al., 2024), we extend the MF-DeepONet framework to capture the structural response of tunnel linings subjected to external loads, aiming to achieve effective fusion between numerical simulations and monitoring data. However, a major limitation in real-world tunnel operations is that external loads are typically unknown, which greatly restricts the applicability of the approach.

To address this challenge, this study proposes an advanced Multi-Fidelity Deep Operator Network (MF-DeepONet) framework augmented with a generative adversarial network (GAN) to simultaneously identify external loads and reconstruct structural responses during tunnel service. Specifically, we introduce a GAN module in which the generator takes displacement measurements at limited points as input and predicts the corresponding external loads. The discriminator is designed to distinguish between two types of predicted loads: (1) those generated from simulated displacements, and (2) those generated from real displacement measurements. The generator is trained on simulation data and further refined through adversarial training, enabling it to produce load predictions from real measurements that closely follow the distribution patterns learned from simulations.

The predicted external loads obtained via the GAN module are then fed into the MF-DeepONet framework developed in Chen Xu et al. (2024) for subsequent reconstruction of the full displacement field. A full-scale test on a quasi-rectangular shield tunnel (QRST) lining structure is used to validate the proposed framework. The results demonstrate that the enhanced MF-DeepONet not only successfully identifies the unknown external loads but also reconstructs displacement fields with high accuracy. The proposed method offers a promising solution for efficient tunnel diagnosis, with the potential to significantly reduce monitoring costs while enhancing safety and resilience.

2. METHODOLOGY

To achieve accurate identification of external loads and reliable structural response prediction of tunnel linings, we propose a multi-fidelity Deep Operator Network (MF-DeepONet) framework enhanced with a Generative Adversarial Network (GAN). As illustrated in Figure 1, the overall workflow consists of the following key steps:

(1) Data Preparation and Pre-processing

A large low-fidelity dataset $\mathcal{T}_L = \{u_L, y_L, s_L(u)(y)\}$ is generated from a validated finite element model under a wide range of external loading combinations. In parallel, a high-fidelity dataset $\mathcal{T}_H = \{u_H, y_H, s_H(u)(y)\}$ is obtained from laboratory tests, representing real-world measurements. The data structure and preprocessing procedures follow the triplet form in Chen Xu et al. (2024). In this context, *u* denotes the external load, *y* is the spatial coordinate, and *s(u)(y)* represents the displacement response at location *y* under the load scenario *u*.

(2) GAN for Load Prediction

A GAN is employed as the core tool for inverse analysis, i.e., external load prediction. The generator, implemented as a fully connected neural network, takes sparse displacement measurements as input and outputs the corresponding external load. The discriminator, which is also a fully connected neural network, evaluates loads from two sources: the predicted load generated by the generator and the load obtained from laboratory measurements. Its objective is to distinguish between these two types of loads. The generator is trained not only through supervised learning on simulation data, but also through adversarial feedback from the discriminator. This dual training strategy enables the generator to produce load distributions from real displacement inputs that exhibit similar patterns to those from simulation. It is important to note that the true external loads corresponding to real measurement data are unknown during training process and thus cannot be used directly for supervised training. In contrast, training a neural network solely on simulated data without incorporating the discriminator typically results in poor generalization to experimental data and often yields unrealistic and highly noisy load predictions.

(3) MF-DeepONet Training for Full-Field Displacement Prediction

The multi-fidelity DeepONet architecture follows the approach introduced in C Xu et al. (2024). The low-fidelity subnet learns the general physical behavior embedded in numerical simulations, while the residual subnet captures the nonlinear correlation between simulation and real-world observations. Supported by abundant simulated data, the trained MF-DeepONet can reconstruct the full displacement field based on only limited real displacement measurements. A key distinction from the previous framework lies in the treatment of high-fidelity loads u_H: in this study, they are not directly measured but inferred through GAN-based inverse analysis. The true experimental loads are used only for validation and are not involved in training.

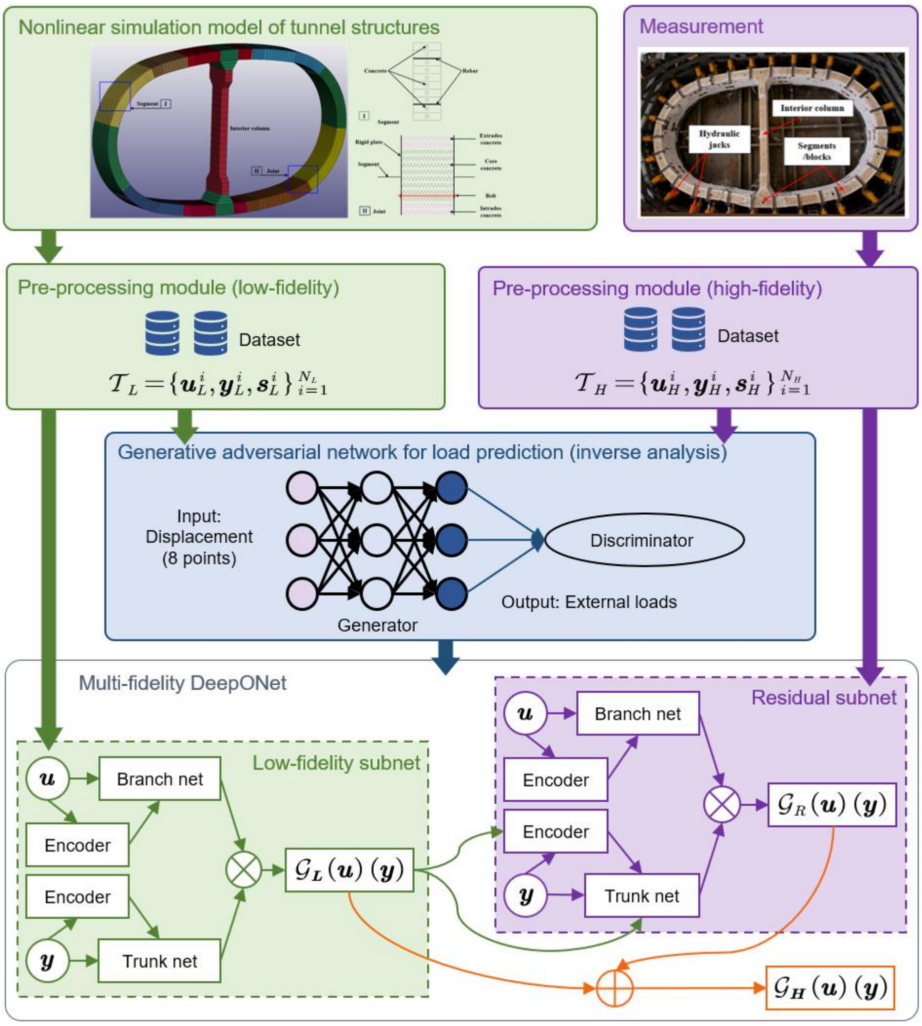


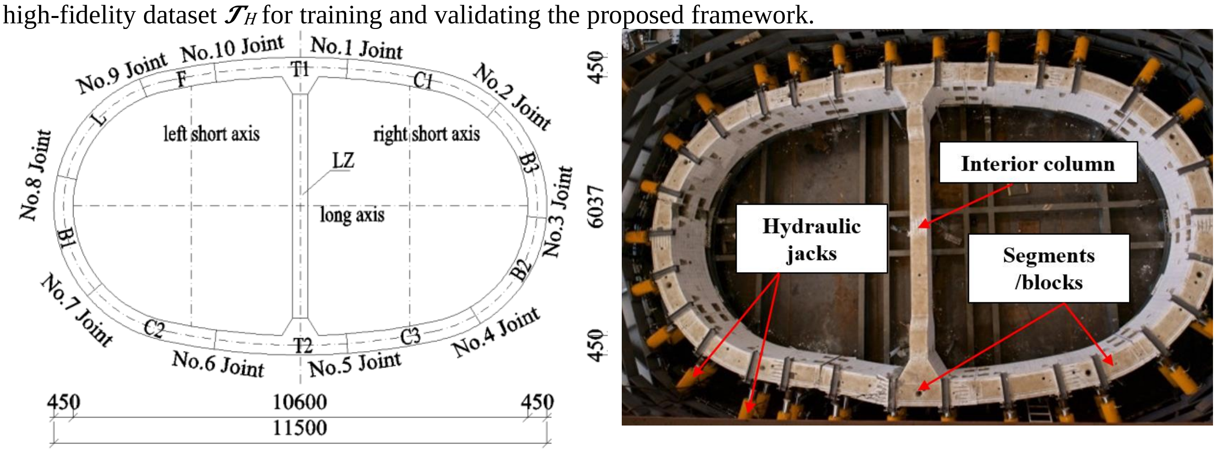
Figure 1. *Illustration of the proposed multi-fidelity DeepONet framework with an integrated generative adversarial network for external load and displacement field prediction, which is an extension of the work in C Xu et al. (2024).*

3. IMPLEMENTATION OF THE PRESENTED APPROACH

3.1. Generation of the high-fidelity dataset: Quasi-rectangular segmental tunnel (QRST) tests

To validate the proposed approach, we use a quasi-rectangular shield tunnel (QRST) project as a representative case. The QRST features a non-circular cross-section designed to optimize underground space utilization in urban environments. The lining structure has an outer dimension of 11.5 m (width) × 6.937 m (height) and consists of ten precast concrete segments and an interior column. Each segment is 1.2 m wide and 0.45 m thick, while the interior column is 0.7 m wide and 0.35 m thick (Liu, Liu, Yuan, et al., 2018; Liu, Ye, et al., 2018).

A full-scale experimental test, as shown in Figure 2, was previously conducted to examine the mechanical performance and failure process of the QRST lining under overburden loading conditions (Liu, Liu, Ye, et al., 2018). Thirty load points were applied across the ring, divided into three groups (P1, P2, and P3) to simulate diverse loading combinations. Displacements at 20 locations around the structure were recorded during 23 load-bearing states, covering the transition from elastic deformation to ultimate failure. This test provides a valuable high-fidelity dataset $\mathcal{T}_H$ for training and validating the proposed framework.



a) QRST geometry b) Photo of full-scale test

Figure 2. *Full-scale test of QRST.*

3.2. Generation of low-fidelity dataset: Numerical modeling

As shown in Figure 3, a validated macro-scale finite element model of the QRST lining was developed using LS-DYNA to simulate the full range of structural responses under varying external loads (Liu et al., 2022; Wu et al., 2012; Zhao et al., 2017). The model incorporates both geometric and material nonlinearities. Segments are modeled using layered thick shell elements, with concrete and reinforcement layers explicitly represented based on material test data and the Chinese code GB 50010-2010 (Chinese Standard, 2002). Longitudinal joints are modeled using a rigid-plate-spring system, consisting of nonlinear zero-length springs to simulate concrete compression and bolt tension behavior.

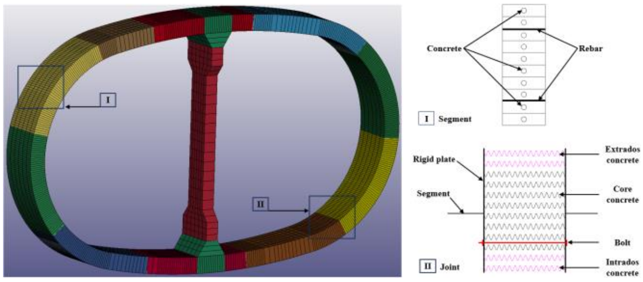


Figure 3. *Illustration of macro-level nonlinear structural model.*

To generate the low-fidelity dataset $\mathcal{T}_L$ for the MF-DeepONet model, a parametric study was conducted by varying the load magnitudes of P1, P2, and P3 from 150 kN to 750 kN in 100 kN increments, resulting in 343 loading scenarios. After filtering out unstable cases, a total of 302 valid simulations were retained. The resulting displacement fields were extracted at multiple locations (totally 519 points) and used as inputs for the low-fidelity training process. This numerical model effectively captures the multi-stage deformation of the QRST structure, including the transition from elastic to plastic behavior and the formation of plastic hinges, as verified by comparisons with full-scale test results.

3.3. Inverse analysis of the tunnel lining: predicting the unknown external loads

Figure 4 shows the spatial distribution of 20 displacement measurement points used in the experiment. Among them, data from 8 orange points are used as inputs to the GAN generator for predicting the corresponding external loads.

The generator is composed of four hidden layers, each with 20 neurons. The discriminator consists of two hidden layers, also with 20 neurons each. Both networks use the LeakyReLU activation function and are optimized using the Adam optimizer with a learning rate of 0.001 and a batch size of 80. After 500 epochs, the training converges. The predicted loads generated by the GAN are then compared to the experimentally measured loads. The resulting coefficient of determination R^2 reaches 0.7378, which is considered acceptable given the limited amount of experimental data.

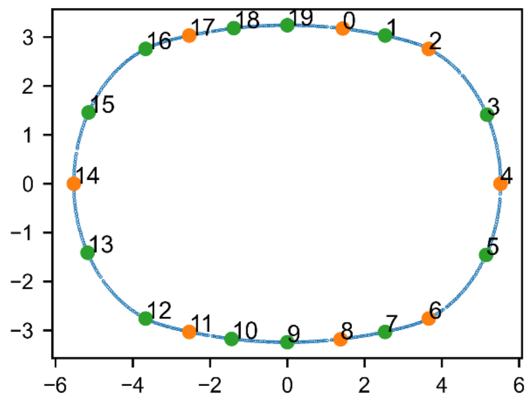


Figure 4. *Layout of displacement measurement points (orange: used for training; green: used for validation).*

3.4. Displacement field reconstruction

Displacement field reconstruction was achieved through training the MF-DeepONet framework. To more clearly illustrate the data used for training each part of the neural network, Table 1 is provided. Notably, the external loads used to train the residual subnet were not the u_H directly measured in the experiment, but rather the u_{pred} inferred via the GAN model described in Subsection 3.3.

Table 1 Input, Output, and Training Data for Each Network Component

Network Component	Input	Output	Training Data
GAN Generator	Displacement at 8 orange points (shown in Figure 4)	Predicted loads (P1, P2, P3)	$\mathcal{T}_{L:}$ u_L, s_L (at 8 points) $\mathcal{T}_{H:}$ u_L, s_H (at 8 points)
Low-fidelity Subnet	u_L, y_L	$\mathcal{G}_L(u_L)(y_L)$	$\mathcal{T}_{L:}$ u_L, y_L (totally 519 points), $s_L(u_L)(y_L)$
Residual Subnet	u_{pred}, y_H	$\mathcal{G}_R(u_{pred})(y_H)$	$\mathcal{T}_{H:}$ u_{pred}, y_H (totally 8 points), $s_H(u_H)(y_H)$

To reconstruct the displacement field at a given load-bearing state *t*, displacement measurements from load states 1 to *t* were required at the 8 sensor locations. The training process was efficient, requiring only 200 epochs. More detailed training settings can be referred to in Chen Xu et al. (2024).

Figure 5 presents the reconstruction results for selected load scenarios. Compared to predictions from the LF subnet, the MF predictions show significantly improved agreement with the experimental results. For the 12 points used to validate the framework's accuracy, the predicted displacements from the MF-DeepONet achieved an R^2 score above 0.8, which is sufficient for practical engineering applications.

Due to the support of extensive numerical simulations, the framework can reconstruct the full displacement field (519 points in total) using measurements from only 8 locations. This demonstrates the strong generalization capability and data efficiency of the proposed approach. Remarkably, despite the GAN-inferred loads not being perfectly accurate, the displacement reconstructions remain highly consistent with the experimental observations.

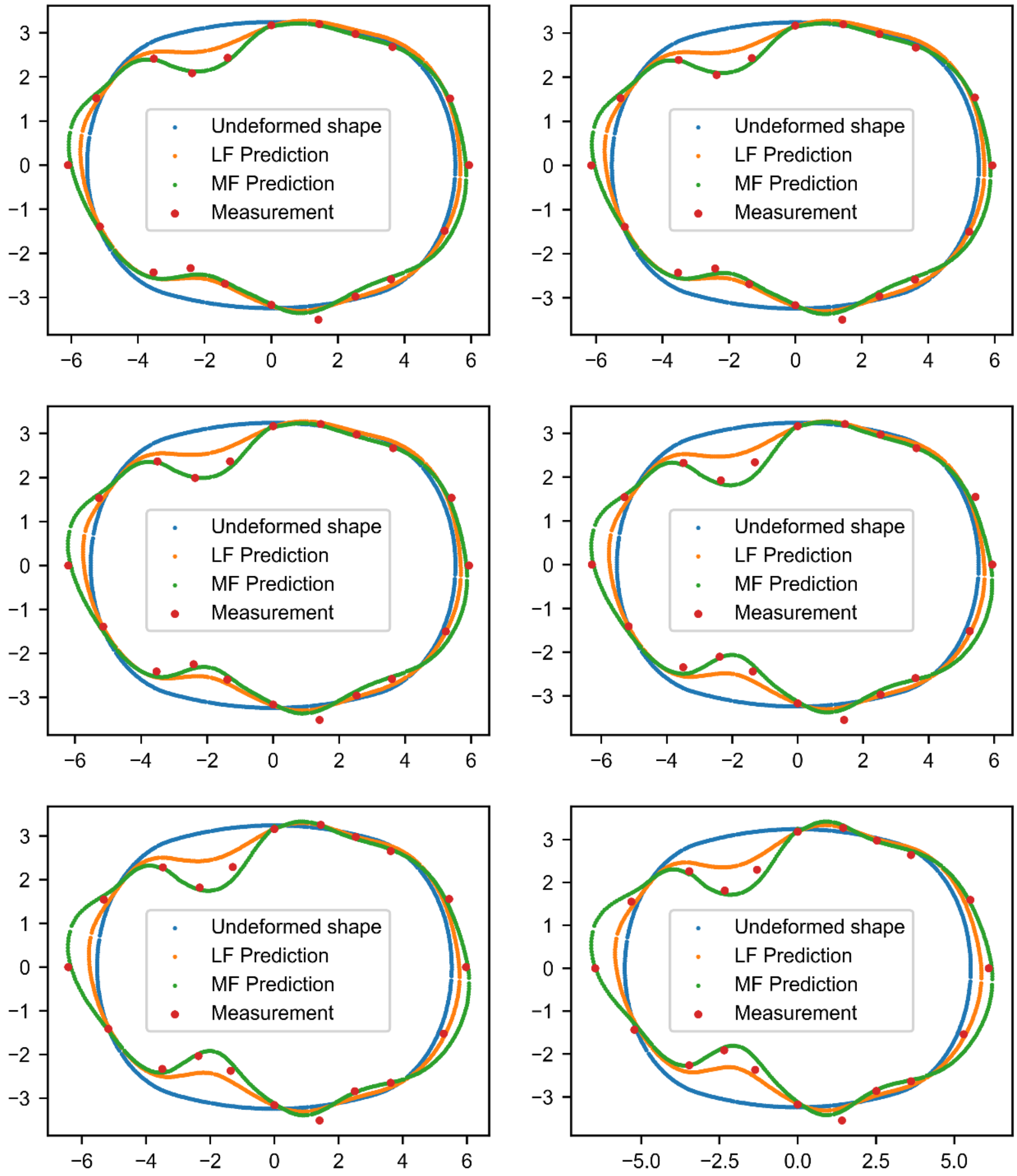


Figure 5. *Predicted displacement fields under different external load scenarios using the proposed framework. The subplots from top-left to bottom-right correspond to load scenarios 14 to 19, respectively.*

4. CONCLUSION

This study presents a multi-fidelity Deep Operator Network (MF-DeepONet) framework enhanced with a Generative Adversarial Network (GAN) for external load prediction and displacement field reconstruction of tunnel structures. By combining simulation-generated low-fidelity data and sparse experimental measurements, the framework enables accurate forward prediction of structural responses and inverse identification of external loads, even in the absence of direct load labels. The GAN component improves load inference by learning realistic distributions aligned with simulation physics.

Validation on a full-scale quasi-rectangular shield tunnel test confirms the framework's effectiveness in reconstructing displacement fields with high accuracy and robustness. The predicted displacements show strong agreement with experimental measurements, achieving an average R^2 value above 0.8 across multiple load states. Additionally, the GAN-inferred load distributions remain physically consistent with simulation patterns, enabling reliable inverse identification.

While these results are promising, the transferability of the proposed approach to different tunnel geometries, lining types, or load scenarios remains an open question. Moreover, the GAN module may need retraining or fine-tuning when applied to significantly different structural or loading conditions, depending on the degree of deviation from the original training domain. Future work will explore these aspects and evaluate the framework's adaptability across various tunnel types and operational environments.

Overall, this approach offers a promising direction for integrating physics-based modeling and operator learning in underground infrastructure monitoring, supporting real-time evaluation and maintenance decision-making with reduced dependence on dense sensor networks.

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