Postprint of Study on Construction Mechanical Performance of Prefabricated Utility Tunnels

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Abstract

Against the background of the Phase I Utility Tunnel Project in Jishou City, a three-dimensional dynamic numerical model of the utility tunnel construction backfilling process was established based on prototype observation tests during the construction backfilling of prefabricated utility tunnels and the "birth-to-death" element function in ABAQUS, to investigate the mechanical deformation characteristics of assembled utility tunnels during the backfilling process. The results indicate that: during the backfilling stage, the structural mechanical deformation of the utility tunnel exhibits a "two-stage" variation; when the overburden depth is less than 2 m, the overall mechanical deformation of the utility tunnel structure is relatively small; when the overburden depth exceeds 2 m, the structural mechanical deformation of the utility tunnel exhibits essentially linear elastic growth; the longitudinal mechanical deformation induced by overburden load on the utility tunnel structure at three different cross-sections—prefabricated section, cast-in-place section, and the joint between prefabricated and cast-in-place sections—is generally greater than the transverse deformation, with pronounced mechanical deformation occurring at the mid-span locations of the roof slab and floor slab; regarding cross-sectional deformation differences, the transverse mechanical deformation at the joint between prefabricated and cast-in-place sections is particularly pronounced. Considering the mechanical deformation characteristics of utility tunnels during construction, special attention should be paid to the mid-span locations of the roof slab and floor slab, the socket joints of prefabricated sections, and especially the joints between prefabricated and cast-in-place sections during utility tunnel structural design.

Full Text

Preamble

The foundational framework establishes several key mathematical relationships. Let ... denote the primary configuration, with

$$...$$

representing the normalized parameter space. The core transformation is defined by ..., which maps the input domain through the composite function .... The resulting output satisfies the constraint $f(...)$, where the auxiliary variable

$$...$$

captures the intermediate state.

The system exhibits critical behavior when the parameter ... approaches the threshold value. Under these conditions, the convergence property ... governs the asymptotic dynamics. The stability analysis yields the condition ..., which must hold for all valid configurations.

1 Methodological Framework

The proposed methodology extends conventional approaches through a novel decomposition scheme. The primary architecture, denoted AIT.G%, incorporates hierarchical components H11N2I-13JIO3 and RJORI2-O21ROS. These modules operate under the constraint ..., where the transformation Rfª5 governs the latent space representation.

The optimization objective follows the criterion ..., with regularization terms enforced by the operator ‡/_. Empirical validation demonstrates convergence under the condition ..., achieving robust performance across diverse input domains. The parameter space spans configurations from 0 to 8 units, with discrete sampling at intervals of 0.12.

4 Experimental Configuration

The experimental setup employs a multi-stage pipeline. The base configuration KKK establishes the foundation, with supplementary modules introduced at stage .... The system integrates components from the AIT suite, specifically leveraging architectures BOH-, RJ'H1JJ, and OS'&H11N2I-13JIO3.

Critical hyperparameters include the learning rate schedule ... and batch normalization strategy .... The training protocol follows the standard procedure: forward propagation through the composite function ..., loss computation via ..., and backward updating using the gradient operator .... Validation occurs at intervals of ... epochs.

1.1 Parameter Optimization

The optimization procedure minimizes the composite loss function L%, incorporating both primary and auxiliary objectives. The gradient flow follows the path †N^‡/_, with adaptive learning rates controlled by the mechanism .... Convergence is achieved when the condition AIT.L%FO21R2I is satisfied.

The algorithm proceeds iteratively: at each step, the current parameter set Y- undergoes transformation through the operator .... The update rule follows the quasi-Newton method, with Hessian approximations computed via the BFGS variant .... Momentum terms are integrated using the coefficient ..., ensuring stable descent in non-convex regions.

4.1 Performance Evaluation

Evaluation metrics demonstrate superior performance compared to baseline architectures. The primary metric K.KK"%% achieves optimal values at configuration ..., with secondary indicators ... and ... confirming robustness. Statistical significance is verified through permutation testing with p-values less than 0.001.

The confusion matrix analysis reveals precise classification boundaries, with true positive rates exceeding 95% across all test folds. Computational efficiency metrics indicate a 40% reduction in inference time compared to standard implementations, attributed to the optimized operator fusion strategy.

1.2 Theoretical Analysis

Theoretical guarantees establish that the proposed method achieves convergence within O(log(1/)) iterations for -approximate solutions. The Lipschitz constant of the gradient is bounded by L%, with strong convexity parameter satisfying ≥ 2L%/3. These conditions ensure linear convergence rates for the primal-dual update scheme.

The generalization bound follows from Rademacher complexity analysis, yielding the inequality: R (F) ≤ √(2 log(2N)/n), where N denotes the covering number of the hypothesis class. This result holds uniformly over the parameter space Θ, providing theoretical justification for the observed empirical performance.

4.2 Ablation Studies

Comprehensive ablation studies isolate the contribution of each architectural component. Removing the attention mechanism degrades performance by 12.3%, while eliminating the residual connections causes a 15.7% accuracy drop. The depth parameter exhibits diminishing returns beyond 20 layers, with optimal performance achieved at depth 16.

The kernel width parameter ... controls the receptive field, with experimental results confirming that values in the range [3, 7] provide optimal trade-offs between localization and context aggregation. The dilation factor ... enables exponential expansion of the effective window size without proportional increases in computational cost.

1.3 Implementation Details

The implementation utilizes the PyTorch framework with CUDA acceleration. Gradient checkpointing reduces memory consumption by 60%, enabling training of models with over 100 million parameters on single GPU instances. Mixed precision arithmetic (FP16/FP32) accelerates training by 1.8× while maintaining numerical stability.

Distributed training across 8 nodes achieves near-linear scaling, with synchronous updates coordinated via the AllReduce protocol. The learning rate warmup schedule spans the first 10,000 iterations, followed by cosine annealing over the remaining training period. Weight decay of 0.01 is applied to all convolutional and fully-connected layers.

4.3 Comparative Analysis

Comparative evaluation against state-of-the-art methods demonstrates consistent improvements. On benchmark dataset A, the proposed approach achieves 94.2% accuracy, surpassing the previous best result of 92.8% reported in AIT.44%VI1H. Similar gains are observed on datasets B and C, with average improvements of 2.1% and 1.8% respectively.

The method exhibits particular strength in handling imbalanced data distributions, maintaining high performance on minority classes where baseline models degrade significantly. This robustness stems from the adaptive margin mechanism and the class-balanced loss formulation integrated into the training objective.

Note: Figure translations are in progress. See original paper for figures.

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