Novelty Assessment Report

Paper: Native Adaptive Solution Expansion for Diffusion-based Combinatorial Optimization

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Abstract

One central challenge in Neural Combinatorial Optimization (NCO) is handling hard constraints efficiently. Beyond the two classic paradigms, i.e., Local Construction (LC), which sequentially builds feasible solutions but scales poorly, and Global Prediction (GP), which produces one-shot heatmaps yet struggles with constraint conflicts, the recently proposed Adaptive Expansion (AE) shares the advantages of both by progressively growing partial solutions with instance-wise global awareness. However, existing realizations bolt AE onto external GP predictors, so their solution quality is bounded by the backbone and their inference cost scales with repeated global calls. In this paper, we fundamentally rethink adaptive expansion and make it native to a generative model, acting as its intrinsic decoding principle rather than an external wrapper. We propose NEXCO, a CO-specific masked diffusion framework that turns adaptive expansion into the model's own iterative unmasking process. Specifically, it involves a solution-expansion training procedure with a time-agnostic GNN denoiser, which learns diffusion trajectories between fully masked solutions and ground-truth solutions. With the trained time-agnostic denoiser, we introduce a novel solution expansion scheme at the solving stage, enabling adaptive control over the intermediate solution states. It is achieved by constructing candidate sets according to confidence scores and applying feasibility projection to expand the solution while respecting constraints. In this way, ``adaptive" is not an afterthought but the decoding itself: intermediate diffusion states are meaningful partial solutions and progress is instance-adaptive rather than schedule-bound. Extensive experiments on representative CO problems show that NEXCO achieves approximately 50\% improvement in solution quality and up to $4\times$ faster inference compared to prior state-of-the-art solvers.

Core Task Landscape

This paper addresses: **neural combinatorial optimization with adaptive solution expansion**

A total of **50 papers** were analyzed and organized into a taxonomy with **19 categories**.

Taxonomy Overview

The research landscape has been organized into the following main categories:

- **Solution Construction Paradigms**
- **Solution Improvement and Refinement**
- **Problem-Specific Applications**
- **Unified and Cross-Problem Frameworks**
- **Representation and Encoding**
- **Training and Optimization Strategies**
- **Constraint Handling and Feasibility**
- **Solution Diversity and Exploration**
- **Surveys and Taxonomies**
- **Specialized Techniques and Extensions**

Complete Taxonomy Tree

- neural combinatorial optimization with adaptive solution expansion Survey Taxonomy
- Solution Construction Paradigms
  - Local Construction Methods (5 papers)
  - [7] Self-Improvement for Neural Combinatorial Optimization: Sample without Replacement, but Improvement (Pirnay, 2024) View paper
  - [17] Learning Encodings for Constructive Neural Combinatorial Optimization Needs to Regret (Rui Sun, 2024) View paper
  - [27] Take a Step and Reconsider: Sequence Decoding for Self-Improved Neural Combinatorial Optimization (Pirnay, 2024) View paper
  - [38] Reinforcement Learning for Solving Open Vehicle Routing Problem with Time Window: A Gated Focused Attention Method (Chengda Wen, 2025) View paper
  - [40] A Deep Reinforcement Learning Algorithm Using Dynamic Attention Model for Vehicle Routing Problems (Bo Peng, 2020) View paper
  - Global Prediction Methods (3 papers)
  - [26] Matrix Encoding Networks for Neural Combinatorial Optimization (Kwon, 2021) View paper
  - [30] Flex-Net: A Graph Neural Network Approach to Resource Management in Flexible Duplex Networks (Tharaka Perera, 2023) View paper
  - [31] Graph Q-Learning for Combinatorial Optimization (Victoria M. Dax, 2024) View paper
  - Adaptive Expansion Methods ★ (4 papers)
  - [0] Native Adaptive Solution Expansion for Diffusion-based Combinatorial Optimization (Anon et al., 2026) View paper
  - [28] Accelerating Diffusion-based Combinatorial Optimization Solvers by Progressive Distillation (Huang Junwei, 2023) View paper
  - [43] Neural Combinatorial Optimization by Means of Partial Solution Strategies (Josu Ceberio, 2024) View paper

    - [48] Boosting Cross-problem Generalization in Diffusion-Based Neural Combinatorial Solver via Inference Time Adaptation (Lei Haoyu, 2025) View paper
- Solution Improvement and Refinement
    - Neural Improvement Heuristics (3 papers)
    - [2] Scaling combinatorial optimization neural improvement heuristics with online search and adaptation (Bortolussi, 2025) View paper
    - [9] A Neural-Assisted Combinatorial Optimizer with Adaptive Neighborhood Search (Weile Xu, 2025) View paper
    - [25] Moco: A Learnable Meta Optimizer for Combinatorial Optimization (Tim Dernedde, 2024) View paper
    - Preference Optimization and Regret-Based Learning (1 papers)
    - [13] BOPO: Neural Combinatorial Optimization via Best-anchored and Objective-guided Preference Optimization (Liao Zijun, 2025) View paper
- Problem-Specific Applications
    - Vehicle Routing Problems (5 papers)
    - [1] Neural combinatorial optimization for real-world routing (Son, 2025) View paper
    - [5] Boosting neural combinatorial optimization for large-scale vehicle routing problems (F Luo, 2025) View paper
    - [16] Online Vehicle Routing With Neural Combinatorial Optimization and Deep Reinforcement Learning (James J. Q. Yu, 2019) View paper
    - [22] Learn to Solve Vehicle Routing Problems ASAP: A Neural Optimization Approach for Time-Constrained Vehicle Routing Problems with Finite Vehicle Fleet (Elija Deineko, 2024) View paper
    - [35] Too Big, so Fail? - Enabling Neural Construction Methods to Solve Large-Scale Routing Problems (Falkner, 2023) View paper
    - Scheduling Problems (7 papers)
    - [12] RCM: A Neural Policy Model With Reconstruction Mechanism to Construct a Solution for the Agile Satellite Scheduling Problem (Ming Chen, 2025) View paper
    - [15] Learning-Guided Rolling Horizon Optimization for Long-Horizon Flexible Job-Shop Scheduling (Li SiRui, 2025) View paper
    - [32] A Heuristic Construction Neural Network Method for the Time-Dependent Agile Earth Observation Satellite Scheduling Problem (Jiawei Chen, 2022) View paper
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    - [36] A Deep Reinforcement Learning Based Solution for Flexible Job Shop Scheduling Problem (B. A. Han, 2021) View paper
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    - [50] Neural Combinatorial Optimization for Stochastic Flexible Job Shop Scheduling Problems (Nuijten, 2024) View paper
    - Other Domain Applications (4 papers)
    - [10] A Learning-Based Assembly Sequence Planning Method Using Neural Combinatorial Optimization With Satisfactory Generalization Ability (Ruiming Hou, 2025) View paper
    - [14] Advancing Differentiable Economics: A Neural Network Framework for Revenue-Maximizing Combinatorial Auction Mechanisms (Pham Mai, 2025) View paper
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    - [46] Active-adaptive construction project management system based on self-organizing maps for optimization of architectural and structural solutions (Yu.V. Zabaykin, 2025) View paper
- Unified and Cross-Problem Frameworks
    - Multi-Problem Generalization (2 papers)
    - [4] UniCO: On unified combinatorial optimization via problem reduction to matrix-encoded general TSP (W Pan, 2025) View paper
    - [21] Routefinder: Towards foundation models for vehicle routing problems (Berto, 2024) View paper
    - Transfer Learning and Uncertainty Handling (2 papers)
    - [20] Leveraging Transfer Learning in Deep Reinforcement Learning for Solving Combinatorial Optimization Problems Under Uncertainty (Achamrah, 2024) View paper
    - [41] Reinforcement Learning Variants for Stochastic Dynamic Combinatorial Optimization Problems in Transportation (Hildebrandt, 2023) View paper
- Representation and Encoding
    - Graph Neural Network Encoders (3 papers)
    - [3] Graph learning for combinatorial optimization: a survey of state-of-the-art (Yun Peng, 2021) View paper
    - [18] Annealing Machine-assisted Learning of Graph Neural Network for Combinatorial Optimization (Loyola Pablo, 2025) View paper
    - [45] Graph-Supported Dynamic Algorithm Configuration for Multi-Objective Combinatorial Optimization (Reijnen, 2025) View paper
    - Generative Flow Networks (1 papers)
    - [19] Adversarial generative flow network for solving vehicle routing problems (Zhang Ni, 2025) View paper
    - Neural Algorithmic Reasoning (1 papers)
    - [23] Tackling GNARLy Problems: Graph Neural Algorithmic Reasoning Reimagined through Reinforcement Learning (Darvariu, 2025) View paper
- Training and Optimization Strategies
    - Supervised and Hybrid Training (1 papers)
    - [47] Learning Heuristics for Combinatorial Optimization Problems with Deep Neural Networks (Hottung, 2023) View paper
    - Meta-Optimization and Algorithm Configuration (1 papers)
    - [33] Learning to balance exploration and exploitation in pareto local search for multi-objective combinatorial optimization (Haotian Zhang, 2022) View paper
- Constraint Handling and Feasibility (1 papers)
    - [44] Geometric Algorithms for Neural Combinatorial Optimization with Constraints (Karalias, 2025) View paper
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    - [24] PolyNet: Learning Diverse Solution Strategies for Neural Combinatorial Optimization (Hottung, 2024) View paper
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  - [37] Layered controller synthesis for dynamic multi-agent systems (Clement, 2023) View paper
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  - [49] COMBINATORIAL OPTIMIZATION OF SYSTEMS OF NEURAL NETWORK CRYPTOGRAPHIC DATA PROTECTION (V. V. Riznyk, 2022) View paper

Narrative

Core task: neural combinatorial optimization with adaptive solution expansion. The field has evolved into a rich ecosystem of approaches that can be organized around several major themes. Solution Construction Paradigms explore how neural models build solutions incrementally or in parallel, with Adaptive Expansion Methods focusing on dynamically growing partial solutions based on learned policies. Solution Improvement and Refinement branches emphasize post-construction enhancement through local search or iterative refinement, while Problem-Specific Applications target domains such as vehicle routing, scheduling, and assembly planning. Unified and Cross-Problem Frameworks seek architectures that generalize across multiple combinatorial tasks, and Representation and Encoding branches investigate how to embed problem structure into neural inputs. Training and Optimization Strategies address learning objectives and sample efficiency, Constraint Handling ensures feasibility, and Solution Diversity and Exploration tackle the balance between exploitation and broad search. Representative works span from early surveys like Machine Learning Combinatorial[8] and Graph Learning Survey[3] to recent scalable methods such as Scaling Neural Heuristics[2] and UniCO[4], illustrating the field's maturation from foundational concepts to large-scale deployment.

Recent activity highlights contrasts between construction-focused and improvement-focused paradigms, with many studies exploring hybrid strategies that combine both. Within the Adaptive Expansion Methods branch, Native Adaptive Solution[0] exemplifies approaches that learn to expand partial solutions step-by-step, adjusting the construction process based on intermediate states. This contrasts with methods like Partial Solution Strategies[43], which emphasize starting from incomplete configurations and filling gaps, and Inference Time Adaptation[48], which tunes policies during deployment rather than purely at training time. Native Adaptive Solution[0] shares the incremental construction philosophy with Progressive Distillation[28] but distinguishes itself by focusing on adaptive decision-making at each expansion step rather than distilling fixed heuristics. Meanwhile, works such as Boosting Large VRP[5] and Neural Real-World Routing[1] push the boundaries of scale and real-world applicability, raising open questions about how adaptive expansion strategies can maintain solution quality and computational efficiency as problem sizes grow. The landscape reflects ongoing exploration of when to construct, when to refine, and how to balance learned flexibility with hard constraints.

Related Works in Same Category

The following **3 sibling papers** share the same taxonomy leaf node with the original paper:

1. Accelerating Diffusion-based Combinatorial Optimization Solvers by Progressive Distillation

Authors: Huang Junwei, Junwei Huang, Sun Zhiqing, Zhiqing Sun, Yang, et al. (7 authors total) | **Year/Venue**: 2023 | **URL**: View paper

Abstract

Graph-based diffusion models have shown promising results in terms of generating high-quality solutions to NP-complete (NPC) combinatorial optimization (CO) problems. However, those models are often inefficient in inference, due to the iterative evaluation nature of the denoising diffusion process. This paper proposes to use progressive distillation to speed up the inference by taking fewer steps (e.g., forecasting two steps ahead within a single step) during the denoising process. Our experimen...

Relationship Analysis

Both papers belong to the Adaptive Expansion Methods category, focusing on progressive solution-building approaches for neural combinatorial optimization. They share the use of diffusion-based models for CO problems like TSP, with both aiming to improve inference efficiency while maintaining solution quality. However, the original paper (NEXCO) proposes a native adaptive expansion framework with masked diffusion and time-agnostic denoising that directly constructs partial solutions, whereas the candidate paper focuses on accelerating existing diffusion solvers (DIFUSCO) through progressive distillation to reduce inference steps without fundamentally changing the solution construction paradigm.

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2. Neural Combinatorial Optimization by Means of Partial Solution Strategies

Authors: Josu Ceberio, Andoni I. Garmendia, Alexander Mendiburu, A. Mendiburu | **Year/Venue**: 2024 | **URL**: View paper

Abstract

N/A

Relationship Analysis

Both papers belong to the Adaptive Expansion Methods category, focusing on progressive solution-building approaches with instance-aware guidance for neural combinatorial optimization. They share the common goal of iteratively expanding partial solutions while maintaining feasibility and global awareness. However, the original paper (NEXCO) proposes a native diffusion-based framework that embeds adaptive expansion directly into a masked diffusion process with time-agnostic denoising, while the candidate paper appears to focus on general partial solution strategies without the specific diffusion-based mechanism or the native integration approach that characterizes NEXCO.

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3. Boosting Cross-problem Generalization in Diffusion-Based Neural Combinatorial Solver via Inference Time Adaptation

Authors: Lei Haoyu, Zhou, Kaiwen, Li, Yinchuan, et al. (9 authors total) | **Year/Venue**: 2025 | **URL**: View paper

Abstract

Diffusion-based Neural Combinatorial Optimization (NCO) has demonstrated effectiveness in solving NP-complete (NPC) problems by learning discrete diffusion models for solution generation, eliminating hand-crafted domain knowledge. Despite their success, existing NCO methods face significant challenges in both cross-scale and cross-problem generalization, and high training costs compared to traditional solvers. While recent studies on diffusion models have introduced training-free guidance approa...

Relationship Analysis

Both papers belong to the Adaptive Expansion Methods category, employing diffusion-based approaches for neural combinatorial optimization with progressive solution construction. They overlap in using diffusion models to iteratively refine partial solutions with global awareness, but differ fundamentally in their expansion mechanisms: the original paper (NEXCO) introduces a native masked diffusion framework with time-agnostic denoising and feasibility projection that embeds adaptive expansion directly into the generative process, while the candidate paper (DIFU-Ada) focuses on inference-time adaptation through energy-guided sampling and recursive renoising-denoising for zero-shot cross-problem transfer, building upon existing pre-trained diffusion solvers rather than redesigning the core diffusion architecture.

Contributions Analysis

Overall novelty summary. The paper proposes NEXCO, a masked diffusion framework that integrates adaptive expansion directly into the generative model's iterative unmasking process rather than relying on external global predictors. It sits within the Adaptive Expansion Methods leaf, which contains only four papers including this one. This is a relatively sparse research direction compared to more crowded areas like Vehicle Routing Problems (five papers) or Scheduling Problems (seven papers), suggesting that adaptive expansion as a paradigm is still emerging and less explored than traditional sequential or one-shot approaches.

The taxonomy tree reveals that Adaptive Expansion Methods is one of three construction paradigms alongside Local Construction Methods (five papers) and Global Prediction Methods (three papers). Neighboring branches include Solution Improvement and Refinement, which focuses on post-construction enhancement rather than initial building strategies, and Representation and Encoding, which addresses how problem structure is embedded. The scope note for Adaptive Expansion explicitly excludes purely sequential construction without global awareness and one-shot prediction, positioning this work at the intersection of progressive building and instance-aware guidance. The sibling papers in this leaf explore related themes: partial solution strategies, inference-time adaptation, and progressive construction, but the taxonomy structure suggests these approaches remain distinct from the diffusion-based formulation proposed here.

Among the thirteen candidates examined through limited semantic search, none clearly refute any of the three contributions. Contribution A (Native Adaptive Expansion paradigm) examined ten candidates with zero refutable matches, Contribution B (CO-specific masked diffusion with time-agnostic denoiser) examined two candidates with zero refutations, and Contribution C (solution expansion inference with feasibility projection) examined one candidate with zero refutations. This suggests that within the limited search scope, the specific combination of diffusion-based generative modeling and native adaptive expansion appears relatively unexplored. However, the small candidate pool (thirteen total) means the analysis cannot rule out relevant prior work beyond the top semantic matches examined.

Based on the limited literature search covering thirteen candidates, the work appears to occupy a novel position by making adaptive expansion intrinsic to a diffusion model rather than an external wrapper. The sparse population of the Adaptive Expansion Methods leaf and the absence of refuting candidates within the examined scope suggest potential novelty, though the analysis acknowledges it does not cover the full breadth of diffusion-based combinatorial optimization or masked generative modeling literature beyond the top semantic matches.

This paper presents **3 main contributions**, each analyzed against relevant prior work:

Contribution 1: Native Adaptive Expansion (NAE) paradigm for diffusion-based CO

Description: The authors introduce a framework that embeds adaptive expansion directly into the diffusion process as an intrinsic decoding principle, rather than as an external wrapper around global predictors. This makes intermediate diffusion states meaningful partial solutions with instance-adaptive progress.

This contribution was assessed against **10 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Continuous-time Discrete-space Diffusion Model for Recommendation

URL: View paper

Brief Assessment

Continuous-time Discrete Diffusion[60] focuses on recommendation systems using discrete-space diffusion with masking operations on user-item interactions, not combinatorial optimization problems with adaptive expansion mechanisms.

2. Optimizing medical image report generation through a discrete diffusion framework

URL: View paper

Brief Assessment

Medical Report Generation[56] focuses on medical image report generation using discrete diffusion, not combinatorial optimization. The candidate addresses a completely different domain (medical imaging) with different objectives (text generation from images) rather than CO problems like TSP or MIS.

3. Graphically structured diffusion models

URL: View paper

Brief Assessment

Graphically Structured Diffusion[59] focuses on imposing graphical model structure into diffusion models for general algorithmic tasks (sorting, sudoku, matrix factorization), not on combinatorial optimization with adaptive expansion mechanisms. The candidate does not address adaptive expansion as an intrinsic decoding principle for CO problems.

4. Boosting Generalization in Diffusion-Based Neural Combinatorial Solver via Inference Time Adaptation

URL: View paper

Brief Assessment

Boosting Generalization Diffusion[53] focuses on inference-time adaptation for zero-shot cross-problem transfer (e.g., TSP to PCTSP/OP) using energy-guided sampling and recursive renoising-denoising, not on embedding adaptive expansion as an intrinsic decoding principle within the diffusion process itself.

5. Diffusion model-based multiobjective optimization for gasoline blending scheduling

URL: View paper

Brief Assessment

Gasoline Blending Diffusion[58] applies diffusion models to gasoline blending scheduling, a continuous production optimization problem with mixed-integer constraints. It does not address combinatorial optimization on graphs or adaptive expansion mechanisms for discrete solution construction.

6. Inference-time scaling of diffusion models through classical search

URL: View paper

Brief Assessment

Inference-time Scaling[51] focuses on inference-time control and search strategies for diffusion models in general domains (planning, RL, image generation), not on combinatorial optimization. The candidate does not address adaptive expansion as an intrinsic decoding principle for CO problems.

7. Scalable discrete diffusion samplers: Combinatorial optimization and statistical physics

URL: View paper

Brief Assessment

Scalable Discrete Diffusion[57] focuses on memory-efficient training methods for discrete diffusion models in combinatorial optimization and statistical physics, not on adaptive expansion as an intrinsic decoding principle. The candidate addresses memory scaling through RL-based and importance sampling objectives, while the original paper embeds adaptive expansion directly into the diffusion unmasking process.

8. Fast t2t: Optimization consistency speeds up diffusion-based training-to-testing solving for combinatorial optimization

URL: View paper

Brief Assessment

Fast t2t[52] focuses on optimization consistency training for diffusion models to enable fast one-step generation, not on embedding adaptive expansion as an intrinsic decoding principle within the diffusion process itself.

9. Conditional diffusion-based parameter generation for quantum approximate optimization algorithm

URL: View paper

Brief Assessment

Conditional Diffusion QAOA[55] focuses on quantum approximate optimization parameter generation using diffusion models, not on combinatorial optimization solution construction through adaptive expansion mechanisms.

10. Generation as search operator for test-time scaling of diffusion-based combinatorial optimization

URL: View paper

Brief Assessment

Generation Search Operator[54] focuses on test-time scaling through search-driven generation cycles that combine solution disruption and diffusion sampling, rather than embedding adaptive expansion as an intrinsic decoding principle within the diffusion process itself.

Contribution 2: CO-specific masked diffusion with time-agnostic denoiser

Description: The framework uses a corruption process that masks only selected variables (1s) while preserving unselected ones (0s), coupled with a time-agnostic graph neural network denoiser trained under optimization consistency. This ensures intermediate states remain valid partial solutions aligned with combinatorial feasibility.

This contribution was assessed against **2 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. Information-Theoretic Discrete Diffusion

URL: View paper

Brief Assessment

Information-Theoretic Diffusion[63] focuses on establishing information-theoretic foundations (I-MDSE, I-MDCE relations) for discrete diffusion models and likelihood estimation, not on combinatorial optimization with feasibility-preserving masked diffusion and time-agnostic denoisers for CO problems.

2. Masked Diffusion for Generative Recommendation

URL: View paper

Brief Assessment

Masked Diffusion Recommendation[62] applies masked diffusion to recommendation systems with semantic IDs, not to combinatorial optimization problems. The technical domains and problem formulations are fundamentally different.

Contribution 3: Solution expansion inference scheme with feasibility projection

Description: At inference time, the method progressively expands partial solutions by selecting high-confidence variables and enforcing problem-specific constraints through feasibility projection. This achieves O(Ts) complexity compared to O(Ds·Ts) for wrapper-based approaches while maintaining solution quality.

This contribution was assessed against **1 related papers** from the literature. Papers with potential prior art are analyzed in detail with textual evidence; others receive brief assessments.

1. An AC-Feasible Linear Model in Distribution Networks With Energy Storage

URL: View paper

Brief Assessment

AC-Feasible Linear[61] addresses linear constraint formulation for energy storage in power distribution networks, not combinatorial optimization with diffusion models or progressive solution expansion schemes.

Appendix: Text Similarity Detection

Textual similarity detection checked 16 papers and found 4 similarity segment(s) across 2 paper(s).

The following **2 paper(s)** were detected to have high textual similarity with the original paper. These may represent different versions of the same work, duplicate submissions, or papers with substantial textual overlap. Readers are advised to verify these relationships independently.

1. Generation as search operator for test-time scaling of diffusion-based combinatorial optimization

Detected in: Contribution: contribution_1

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

2. Fast t2t: Optimization consistency speeds up diffusion-based training-to-testing solving for combinatorial optimization

Detected in: Contribution: contribution_1

⚠ **Note**: This paper shows substantial textual similarity with the original paper. It may be a different version, a duplicate submission, or contain significant overlapping content. Please review carefully to determine the nature of the relationship.

References

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