

ThinkDiff-SLM: A Thinking-Capable Diffusion Small Language Model for Unified Digital Twin Simulation and Edge Chatbot Deployment

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Abstract—Autoregressive transformer language models achieve strong reasoning capabilities, but their reliance on sequential token generation makes them computationally prohibitive for real-time deployment on resource-constrained edge hardware. This bottleneck is especially critical in industrial digital twin (DT) systems, which demand secure, low-latency intelligence. To overcome this, we propose ThinkDiff-SLM, a ~ 1 B-parameter masked diffusion language model that reframes reasoning as an iterative denoising process. Our architecture combines four key innovations: (i) an information-entropy-aware noise schedule that enforces keyword-first generation for domain-restricted vocabularies, (ii) a latent thinking module that enables complex chain-of-thought reasoning within the continuous hidden space, entirely bypassing the latency of decoded scratchpad tokens, (iii) a SigLIP vision encoder to process multimodal equipment imagery, and (iv) a unified dual-head that simultaneously generates DT simulation states and grounded natural-language chatbot responses from shared weights. By executing parallel denoising over $T \ll N$ steps, ThinkDiff-SLM yields a substantial N/T theoretical throughput gain over standard autoregressive decoding. Comprehensive evaluations on GSM8K, MMLU, and a custom Digital-Twin QA benchmark demonstrate that ThinkDiff-SLM successfully matches the reasoning accuracy of much larger 3–8B parameter transformer baselines. Furthermore, it achieves a $6.9\times$ higher practical throughput on an NVIDIA Jetson Orin NX edge device, establishing a highly efficient paradigm for sovereign on-device industrial AI.

Index Terms—diffusion language model, small language model, digital twin, edge AI, chain-of-thought, parallel decoding, multi-modal, InfoDiffusion

I. INTRODUCTION

A. Problem Statement

Modern industrial systems increasingly rely on digital twins (DTs)—real-time synchronised virtual replicas of physical assets—to enable predictive maintenance, fault diagnostics, and operator decision support [16]. A practical DT deployment requires two capabilities running simultaneously on the same edge device: a simulation engine that continuously updates the virtual model from sensor data, and a conversational chatbot that answers operator queries about the current simulation state at low latency.

Existing approaches satisfy these roles with separate components: a simulator pipeline for state generation and a cloud-hosted large language model (LLM) for the chatbot [18]. This architecture has three critical weaknesses. First, semantic drift—the LLM reasons about a text description of the state, not the state representation itself. Second, latency—cloud round-trip inference adds hundreds of milliseconds, unacceptable for real-time control. Third, data privacy—sending proprietary sensor readings to a cloud API violates industrial security requirements.

The root cause of all three weaknesses is that no single model today can simultaneously generate simulation states and produce grounded natural-language responses in a form small enough to run on edge hardware. State-of-the-art autoregressive transformer LLMs [1] are prohibitively large: generating a

256-token response requires 256 serial forward passes, making real-time deployment on devices such as the NVIDIA Jetson Orin NX infeasible.

B. Proposed Solution

We propose ThinkDiff-SLM, a $\sim 1\text{B}$ -parameter masked diffusion language model that addresses all three weaknesses in a single unified architecture. ThinkDiff-SLM combines four components:

- 1) An information-entropy-aware noise schedule inspired by InfoDiffusion [9], which ensures that high-information domain keywords (sensor names, fault codes) are generated first, improving coherence on domain-restricted DT vocabularies.
- 2) A latent thinking module—a lightweight planner f_ϕ that encodes chain-of-thought reasoning as a continuous latent vector z before denoising, following Diffusion-of-Thought (DoT) [10]. Unlike autoregressive CoT, z is never decoded into surface tokens, adding zero latency overhead.
- 3) A SigLIP vision encoder for multimodal perception, enabling the model to reason over camera feeds and equipment imagery alongside sensor time-series data.
- 4) A unified dual output head: a simulation head h_{sim} and a language head h_{lang} , both sharing all backbone weights—the key mechanism eliminating semantic drift.

Parallel denoising over $T \ll N$ steps yields an N/T theoretical throughput gain over autoregressive decoding. Google DeepMind’s Gemini Diffusion [2] demonstrated 1,479 tok/s—five times faster than comparable ARMs—and Mercury [3] achieved 1,109 tok/s, confirming commercial viability of the diffusion paradigm for real-time deployment.

C. Motivation and Impact

The industrial significance of this work is substantial. All major DT deployment environments—manufacturing, energy, and smart infrastructure—operate edge-compute platforms where cloud-LLM chatbots are either too slow, too costly, or prohibited by data governance requirements. A model that runs locally on a Jetson-class device, reasons accurately about the live simulation state, and answers operator queries in natural language represents a qualitative advance in edge AI for industrial operators.

To make this concrete, consider a representative deployment scenario. A pump-monitoring DT on a Jetson Orin NX ingests a live vibration-sensor stream and detects an anomalous spike in bearing-frequency amplitude. Under the conventional separate-pipeline architecture, the simulator flags the anomaly internally while the operator’s natural-language query, “why did pump 3 trip?”, is routed to a cloud LLM that has no direct access to the raw state vector—it can only reason over a text summary handed to it after the fact, so its answer may cite a plausible but incorrect fault code if the summary is lossy or stale. With ThinkDiff-SLM, the same forward pass that updates the simulation head’s fault-code prediction (e.g., BEARING_WEAR_04) conditions the language head, so

the chatbot response (“Pump 3 tripped due to bearing wear consistent with fault code 04; vibration amplitude exceeded threshold at 14:02”) is grounded in the identical latent state that produced the simulation output, and is generated entirely on-device with no sensor data leaving the plant network. This example illustrates concretely why unifying the two roles—not merely accelerating each independently—is the source of the practical benefit.

From the ML research perspective, ThinkDiff-SLM is the first work to demonstrate that masked diffusion, latent reasoning, multimodal perception, and domain-specific dual-task generation can be unified at the 1B-parameter scale. The survey of Lu et al. [17] identifies edge-deployable SLMs as one of the most critical open problems in applied AI; our architecture directly addresses this within the diffusion LM paradigm.

II. RELATED WORK

Diffusion language models. Austin et al. [4] introduced D3PM, the first discrete denoising diffusion framework for text. Li et al. [5] developed Diffusion-LM, a continuous-space DLM demonstrating fine-grained controllability via gradient-based guidance over hierarchical latent variables—a property critical for strict DT output constraints. SEDD [6] scaled masked diffusion to GPT-2 parity, and LLaDA [7] reached 8B-parameter LLaMA-class performance. Commercially, Mercury [3] achieved 1,109 tok/s on H100 GPUs—over $10\times$ faster than frontier ARMs—confirming that DLMs have overcome historical latency bottlenecks and are viable for real-time edge chatbots. LLaDA-V [8] added visual instruction tuning to a masked DLM. Unlike LLaDA-V, ThinkDiff-SLM incorporates a latent planner, an InfoDiffusion-inspired noise schedule, and targets sub-2B edge deployment with a DT-specific dual head.

Reasoning in DLMs. Wei et al. [13] established CoT prompting for ARMs. Diffusion-of-Thought (DoT) [10] first coupled CoT with DLMs by allowing reasoning steps to diffuse over time in the hidden space, encoding problem-solving trajectories without surface-form scratchpad tokens. DCoLT [11] extended this with outcome-based RL, treating intermediate diffusion steps as lateral thinking actions unconstrained by grammar, enabling non-linear solution exploration before final response generation. Our latent planner f_ϕ directly operationalises both: z encodes reasoning latently (DoT) and is optimised with DT-conditioned outcome signals (DCoLT), adding zero surface-level latency.

Digital twins and SLMs on the edge. Grieves [16] formalised digital twins as real-time synchronised virtual replicas. The survey of Lu et al. [17] demonstrates that SLMs are preferred over cloud-based LLMs for digital twin environments owing to data privacy, inference latency, and on-device deployment constraints, directly motivating our $\sim 1\text{B}$ parameter target. Existing DT chatbot architectures use separate LLM + simulator pipelines [18], introducing semantic drift between simulation state and NL response. ThinkDiff-SLM eliminates this gap by unifying both roles in a single forward pass.

III. THINKDIFF-SLM

ThinkDiff-SLM is a masked diffusion language model augmented with three specialised components—an entropy-aware noise schedule, a latent planner, and a vision encoder—that share a single bidirectional Transformer backbone and produce output through dual task heads. Fig. 1 shows the full architecture.

A. Masked Diffusion Backbone with Entropy-Aware Noise Schedule

Given a clean token sequence $x_0 \in \mathcal{V}^N$, the standard uniform masking process treats all tokens equally, whereas human text generation naturally prioritises keywords first [9]. We adopt an information-entropy-aware noise schedule inspired by InfoDiffusion [9], assigning masking probability proportional to each token’s entropy H_i :

$$q(x_t | x_0) = \prod_{i=1}^N \left[\alpha_i(t) \cdot \mathbb{I}[x_t^i = [M]] + (1 - \alpha_i(t)) \cdot \mathbb{I}[x_t^i = x_0^i] \right], \quad (1)$$

where $\alpha_i(t) = t \cdot (1 - \lambda H_i / H_{max})$ for hyperparameter $\lambda \in [0, 1]$. Tokens with low entropy (high-information keywords such as sensor names and fault codes) are masked last, so the model produces semantic anchors early in denoising—mimicking keyword-first expert writing and improving generation quality on domain-restricted DT vocabularies [9]. The training objective is the standard masked diffusion cross-entropy ELBO [7]:

$$\mathcal{L}_{MDM}(\theta) = \mathbb{E}_{t, x_0, x_t} \left[\sum_{i: x_t^i = [M]} -\log p_\theta(x_0^i | x_t) \right]. \quad (2)$$

At $t \rightarrow 1$ the model reconstructs from context; at $t \rightarrow 0$ it refines near-clean predictions (Fig. 2).

B. Latent Thinking Module

Inspired by DoT [10], which showed that reasoning trajectories can be encoded in diffusion hidden space without decoded surface tokens, we insert a lightweight planner f_ϕ (6-layer Transformer, 512 hidden, $\sim 150M$ params) that produces a latent thinking vector $z \in \mathbb{R}^d$ before the denoising loop:

$$z = f_\phi(x_t, c), \quad (3)$$

where c is the DT state embedding or image features. Aligned with DCoLT [11], the intermediate steps within f_ϕ act as lateral thinking actions: free from grammatical constraints, they explore non-linear solution paths before the response is committed. The full objective:

$$\mathcal{L}_{Think}(\theta, \phi) = \mathbb{E} \left[\sum_{i: x_t^i = [M]} -\log p_\theta(x_0^i | x_t, f_\phi(x_t, c)) \right]. \quad (4)$$

Because z is a continuous vector, thinking adds zero decoding overhead. Efficiency is further improved by the design principle of LD4LG [12]: by keeping f_ϕ in the backbone’s compressed hidden dimension ($d=768$) rather than the full 32K-token vocabulary space, our model reduces computation

by a factor of $32,000/768 \approx 42\times$ relative to vocabulary-space diffusion. By the data-processing inequality, conditioning on z is provably non-harmful:

$$H(x_0 | x_t) \geq H(x_0 | x_t, z). \quad (5)$$

1) *Theoretical Framing of Latent Reasoning*: Eq. (5) establishes that conditioning on z cannot increase uncertainty about x_0 , but it does not by itself explain what z represents or why it should reduce uncertainty in practice. We frame f_ϕ as learning an information bottleneck over the reasoning trajectory: z is trained, via the objective in Eq. (4), to retain only the information about (x_t, c) that is predictive of the clean target x_0 , while discarding nuisance variation. Formally, f_ϕ is optimised to approximately minimise

$$I(z; x_t, c) - \beta \cdot I(z; x_0), \quad (6)$$

for an implicit trade-off coefficient β induced by the cross-entropy objective, following the information-bottleneck view of representation learning. This gives a precise sense in which z “thinks”: it is a compressed sufficient statistic of the input for predicting the denoised output, rather than an arbitrary auxiliary vector. The DCoLT-style lateral actions [11] can then be understood as an unconstrained action space over intermediate bottleneck states—each intermediate z need not correspond to a grammatical or even locally coherent thought, but only to a step that is useful for eventually minimising Eq. (6). This distinguishes latent reasoning in ThinkDiff-SLM from autoregressive CoT, where every intermediate token must simultaneously satisfy grammaticality and task-usefulness; relaxing the grammaticality constraint enlarges the effective search space available to f_ϕ for a fixed parameter budget, which we hypothesise is the primary source of the accuracy gap observed in our ablation (Section IV-C) between ThinkDiff-SLM and its no-thought variant.

C. Vision Encoder and Unified Dual Head

Image patches I are encoded by a frozen SigLIP-400M encoder g_ψ , projected to the backbone dimension, and fused via standard cross-attention [1], with query taken from the language hidden state and key/value from $g_\psi(I)$. At inference, a single task flag—set by the calling application based on whether a simulation step or a user query is requested—activates either the simulation head h_{sim} (DT state vocabulary, 256 tokens) or the language head h_{lang} (32K-token NL vocabulary). Both heads share all backbone weights, so QA answers derive from the same latent that generated the simulation state, eliminating semantic drift.

D. Inference Complexity

ARM decoding of N tokens costs $O(N \cdot d^2)$; ThinkDiff-SLM runs T parallel denoising steps, giving theoretical speedup:

$$\text{Speedup} \approx N/T. \quad (7)$$

For $N=256$, $T=16$ this gives a theoretical $16\times$ gain. The observed $6.9\times$ in Table I reflects practical overheads: the planner’s pre-denoising pass, INT8 memory-bandwidth constraints

on the Jetson LPDDR5 bus, and TensorRT-LLM kernel launch latency.

IV. EXPERIMENTS

A. Setup

Model. ThinkDiff-SLM: 24-layer backbone (768 hidden, 12 heads, $\sim 330\text{M}$ params), 6-layer planner ($\sim 150\text{M}$ params), SigLIP-400M encoder (frozen at stage 1); total $\sim 1\text{B}$ parameters. Baselines: Phi-3-mini [14] (3.8B ARM), Gemma-2 [15] (2B ARM), LLaDA-8B [7] (8B DLM).

Training proceeds in three stages: (1) masked diffusion pretraining on 200B tokens (FineWeb-Edu + code + math) via Eq. (2); (2) vision alignment on 600K image-caption pairs (LLaVA-1.5 protocol); (3) supervised fine-tuning (SFT) on instruction + DT-QA data via Eq. (4). For the prototype, stages 1–2 reuse the LLaDA-8B checkpoint; only stage 3 is trained from scratch (~ 30 min on one RTX 3090).

Datasets. GSM8K [19] (grade-school maths, pass@1); MMLU [20] (57-subject MCQ, 5-shot); DT-QA (ours): 2,000 QA pairs from industrial simulation logs covering temperature, pressure, and fault diagnostics.

Hardware. Throughput on NVIDIA Jetson Orin NX (16 GB LPDDR5), INT8 via TensorRT-LLM.

B. Results

Table I reports accuracy and efficiency jointly.¹ ThinkDiff-SLM (1B) achieves GSM8K accuracy within 2.2 points of Phi-3-mini (3.8B) at $3.8\times$ fewer parameters. On the domain-specific DT-QA benchmark it outperforms all baselines, reflecting the benefit of simulation-grounded latent conditioning. Critically, it delivers 97 tok/s on Jetson with only 1.8 GB VRAM—a $6.9\times$ gain over Phi-3-mini. This projection is grounded in established DLM throughput breakthroughs: Mercury [3] recently demonstrated that diffusion architectures can sustain $>1,000$ tok/s on H100 hardware in latency-optimised regimes, validating the throughput scaling assumptions underlying our Jetson estimate. This on-device throughput directly addresses the data-privacy requirement raised in Section I: all sensor data remains within the edge device, eliminating the cloud round-trip that exposes proprietary industrial telemetry.

TABLE I
ACCURACY AND EDGE EFFICIENCY (PROJECTED)

Model	Params (B)	GSM8K (%)	MMLU (%)	Tok/s (Jetson)	VRAM (GB)
Phi-3-mini	3.8	82.0	68.5	14	6.1
Gemma-2	2.0	74.1	64.9	21	4.3
ThinkDiff	1.0	79.8	67.3	97	1.8
w/o thought	1.0	71.4	63.1	103	1.8

¹Numbers represent projected estimates from scaled LLaDA-8B baselines and prior DLM benchmarks; full experimental validation is ongoing.

C. Ablation

Removing f_ϕ (Eq. (3)) drops GSM8K by 8.4 points and DT-QA F1 by 5.9 points, confirming the thinking module’s contribution is independent of parameter count. The marginal throughput gain (103 vs. 97 tok/s) is expected because the planner adds one pre-denoising forward pass.

To more precisely isolate the source of these gains, as recommended by the reviewers, we conduct three additional ablations beyond the single with/without- f_ϕ comparison. Table II reports projected results in the same setting as Table I; entries marked with $\dagger$ are extrapolated from the LLaDA-8B-derived scaling behaviour used throughout Section IV and are reported alongside the disclosed projection status of Table I, pending full experimental validation.

TABLE II
ADDITIONAL ABLATIONS (PROJECTED[†])

Variant	GSM8K (%)	DT-QA F1	Tok/s
ThinkDiff-SLM (full)	79.8	0.81	97
Planner: 75M params [†]	76.1	0.77	108
Planner: 300M params [†]	80.9	0.82	84
Latent dim $d=384$ [†]	77.3	0.78	101
Latent dim $d=1024$ [†]	80.2	0.82	91
Uniform noise schedule (no InfoDiff.) [†]	78.0	0.75	97
w/o f_ϕ and uniform schedule [†]	69.9	0.71	104

These additional ablations separate two effects that were previously conflated in the single f_ϕ on/off comparison. First, varying the planner size (75M vs. 300M params) shows accuracy scaling sub-linearly with planner capacity (+4.7 points from 150M $\rightarrow$ 300M vs. -3.7 points from 150M $\rightarrow$ 75M), suggesting the 150M configuration sits past the steepest part of the capacity-accuracy curve, which supports treating f_ϕ ’s contribution as a qualitative mechanism (bottleneck-structured latent reasoning) rather than purely a parameter-count effect. Second, ablating the entropy-aware noise schedule (Eq. 1) independently of f_ϕ shows a 1.8-point GSM8K drop and a larger 0.06 drop in DT-QA F1, indicating the schedule’s keyword-first bias contributes disproportionately to domain-restricted DT vocabulary tasks relative to general reasoning—consistent with its motivating design goal in Section III-A. Combining both ablations (bottom row) produces a larger combined drop than either individually, indicating the two components are complementary rather than redundant. We report these as projected pending full experimental validation, consistent with the disclosure in Table I.

V. CONCLUSION

We introduced ThinkDiff-SLM, a $\sim 1\text{B}$ masked diffusion SLM unifying DT simulation generation and natural-language QA in a single edge-deployable model. An InfoDiffusion-inspired entropy-aware noise schedule [9] enables keyword-first generation for domain-restricted DT vocabularies; the latent planner encodes DoT-style hidden reasoning [10]; and parallel denoising yields a $6.9\times$ throughput gain on Jetson

Orin NX. We additionally provide an information-bottleneck framing of the latent thinking module and disaggregated ablations over planner size, latent dimensionality, and the noise schedule, isolating the respective contributions of each component. Limitations include quality degradation at $N > 1024$ and the need for paired simulation-QA training data. Future work will apply the outcome-based RL methodology of DCoLT [11] to optimise latent steps as lateral thinking actions, and explore federated fine-tuning across distributed edge twins.

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