INDEQS: Informed Neural controlled Differential EQuationS

Anonymous authors
Paper under double-blind review

Abstract

Neural Controlled Differential Equations (NCDE) provide a powerful continuous-time framework for forecasting time series, but standard graph-based extensions typically learn spatial structure purely from data, even in settings where a directed graph structure is known a priori. We introduce Informed Neural controlled Differential EQuationS (INDEQS), a graph-based NCDE forecasting method that incorporates prior knowledge of a directed graph at distinct architectural positions. INDEQS separates *inner* mixing of hidden states across graph nodes from *outer* mixing between vector field and control, and offers both a lightweight graph-constrained variant and a more expressive variant, learning additional graph connections from data via adaptive graph convolutions. To systematically study when graph informedness is beneficial in forecasting, we devise a continuous advection simulation on directed graphs, yielding synthetic spatio-temporal datasets with known ground-truth flow structure. We then evaluate INDEQS on two real-world tasks: river discharge forecasting on a hydrological network and traffic flow prediction on PeMS08. Across these synthetic and real-world benchmarks, outer informedness consistently improves mean absolute error over an uninformed NCDE with comparable parameter count, particularly on larger graphs, while inner informedness offers a more parameter-efficient alternative when strict adherence to a known adjacency is desired. A comparison of discrete convolutional and continuous-time decoders further shows that continuous decoders yield better accuracy and greater temporal flexibility on real-world tasks. An implementation of INDEQS and the advection simulation is available at `https://anonymous.4open.science/r/indeqs_tmlr-588E`.

1 Introduction

Effect follows cause. When a problem is represented on a graph, the structure of that graph contains information on how causes at one spatial position are linked to effects at another, and learning physical dynamics from spatial time series data can often leverage this structural information. Schölkopf (2022) describes differential equations as the gold standard for understanding cause-effect structures and highlights how standard machine learning methods give limited treatment to time. Neural Differential Equations (NDEs) Chen et al. (2018) address this gap by learning a hidden state that evolves continuously in time. Neural Controlled Differential Equations (NCDEs) Kidger et al. (2020) extend this further, updating the hidden state continuously from data arriving at different points in time, and Spatio-Temporal Graph NCDEs (STG-NCDEs) Choi et al. (2022) additionally model spatial dependencies through learned node embeddings.

In physical systems with known directed graph structure such as river networks, road networks, and other advective systems, the underlying graph structure carries information on how causes propagate to effects. Existing graph-NCDE approaches learn the spatial structure from data, even when this prior is available.

We propose Informed Neural controlled Differential EQuationS (INDEQS), which inject prior information about an underlying directed graph into the vector field of a Neural Controlled Differential Equation (NCDE) to infer the future dynamics at the vertices. INDEQS comes in two variants — inner and outer informedness — that differ in where the graph structure enters the architecture. Intuitively, the inner position constrains where each node looks across the graph to assemble its update, while the outer position constrains how information from the control is distributed across nodes.

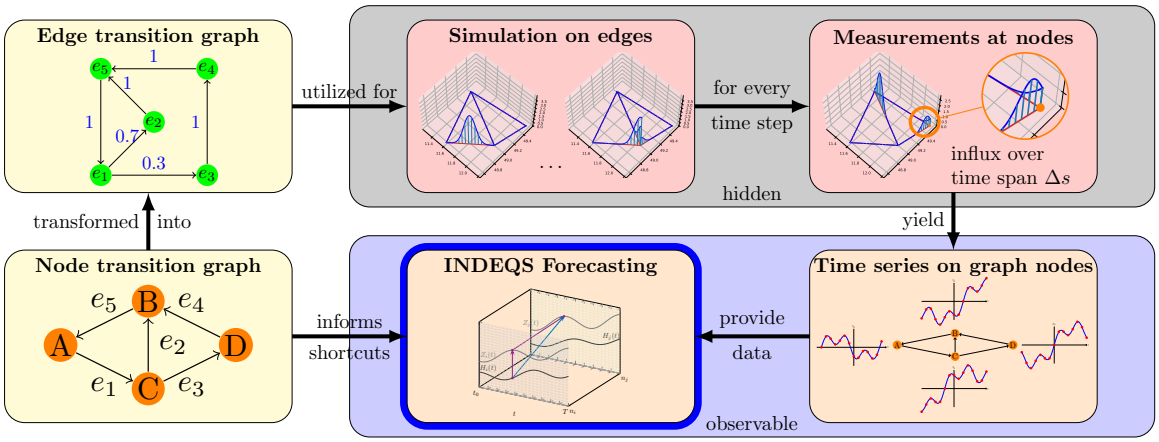


Figure 1: Overview: Starting from an edge transition graph with prior known structure, we simulate advection on the graph edges. Through measurements at vertices, one moves from a description as a continuum on edges to a node-wise time series description of the dynamic. These are used in INDEQS to forecast future state values. Graph information comes via the node transition graph, which can be transformed to the edge transition graph. Edges of the former become nodes in the latter. The first row shows the dynamics on an edge level, the second row on a node level, with the measurements being the bridge from edge representation to node representation. In a real-world application, one cannot observe the propagation along the edges continuously in space over time. One observes the system only at the measuring nodes. INDEQS allows supplementing time series data on nodes with graph information coming from prior knowledge of the dynamics of interest.

To study in a controlled experiment when graph informedness helps, we develop a continuous-time advection simulation on directed graphs, which yields synthetic datasets with known ground-truth flow structure. We then evaluate INDEQS on two real-world tasks: river discharge forecasting on a hydrological network and traffic flow prediction on PeMS08. We restrict our scope to static graphs and use continuous-time models as our primary comparisons; discrete-time baselines are included to situate INDEQS within the broader forecasting literature. Our **contributions** are:

- We introduce INDEQS, a graph-informed NCDE that incorporates prior directed-graph information into the vector field at two architectural positions: inner (mixing across nodes) and outer (mixing between hidden state and control), yielding a parameter-efficient variant that strictly respects the known adjacency and a more expressive, data-adaptive variant.
- We propose a continuous-time advection simulation on directed graphs, which produces synthetic spatio-temporal datasets with known ground-truth flow structure and enables controlled study of when graph informedness benefits forecasting.
- Across synthetic and real-world benchmarks (river discharge and PeMS08 traffic), outer informedness reduces MAE relative to an uninformed NCDE at matched parameter count, with the largest gains on larger graphs; inner informedness offers a parameter-efficient alternative that strictly respects the known adjacency.

Figure 1 shows an overview of the steps from continuous edge advection simulations to node measurements, and the incorporation of the underlying graph structure of the dynamic into the INDEQS forecasting method.

2 Related Work

Spatio-temporal forecasting encompasses a wide range of model families, differing in how they treat the spatial and temporal domains. Ju et al. (2024) give overviews for graph representation learning and Jin et al. (2024) give an overview of graph neural networks for time series forecasting. In Section A.13 we provide a tabular comparison with the most closely related Graph Neural Differential Equation methods to

our work. In the following subsections, we outline different aspects of related works to outline the different treatments of the temporal dimension (discrete versus continuous), and the discrete spatial dimension of graphs versus discretizations of continuous space. Moreover, we address composites of continuous time plus graphs, and conclude with continuous simulations and general applications.

2.1 Graph information in time-discrete forecasting models

Some time-discrete methods learn the graph structure from the given time series data, others rely on a prior given graph. Spatial-Temporal Graph Neural Networks (GNNs) (Wu et al., 2021; Rossi et al., 2020) inform Neural Networks (NNs) with graph information, by combining Message Passing NNs (Gilmer et al., 2017) with Recurrent Neural Networks (RNNs) like Long Short Term Memorys (LSTMs) (Hochreiter & Schmidhuber, 1997) or Gated Recurrent Units (GRUs) (Cho et al., 2014) leading to methods like Diffusion Convolutional Recurrent Neural Networks (DCRNNs) (Li et al., 2018), which depend on a prior known graph structure. Wu et al. (2019) combine Graph Convolutional Networkss (GCNs) (Kipf & Welling, 2017) and dilated convolutions (Yu & Koltun, 2016) for the temporal processing, leading to Graph WaveNet (GWaveNet), which has one variant that learns the graph structure from data and another that uses a prior given graph. Spatial-Temporal Graph Convolutional Networks (STGCNs) (Yu et al., 2018) use graph convolution in both the spatial and the temporal processing, also requiring the prior graph structure. Graph Multi-Attention Network (GMAN) (Zheng et al., 2020) use attention (Kim et al., 2017; Bahdanau et al., 2014) for spatial and temporal processing and does not make use of a given graph topology, only learning graph connectivity from data. Attribute-Augmented Spatiotemporal Graph Convolutional Networks (AST-GCNs) (Zhu et al., 2021) combine graph convolutions on a fixed given graph and GRUs, along with additional node attribute information, while not performing graph adaptions based on data. Attention Based Spatial-Temporal Graph Convolutional Networkss (ASTGCNs) (Guo et al., 2019) use spatial and temporal attention, assuming a given graph structure and only dynamically reweigh edge connections from data. Xiao et al. (2025) use self-attention and learnable node-embeddings to capture graph dynamics and GRUs as the temporal processing.

2.2 Time-continuous models

The seminal work of NDEs (Chen et al., 2018), along with (Funahashi & Nakamura, 1993), allow continuous layer depth which can be arranged to reflect continuous time to align the data time dimension with the model's internal, virtual time dimension. To naturally adapt to later incoming data points, the notion of Controlled Differential Equations (CDEs) is used in NCDEs (Kidger, 2021), allowing learning path-dependent maps from path-space to path-space. The control path construction and their properties is explored in (Morrill et al., 2021) and (Morrill et al., 2022). Walker et al. (2024) introduce a training method to increase efficiency of NCDEs using rough path theory (Lyons et al., 2007). Rubanova et al. (2019) and Dupont et al. (2019) augmented Neural Ordinary Differential Equations (NODEs). Jhin et al. (2024) use attention on the output of an NCDE together with the data path. An overview over different NDE models on time series tasks is provided by Oh et al. (2025).

2.3 Graph time-continuous models

The continuous methods can be extended to allow treatment of time series on graphs. Poli et al. (2021) introduce spatial inductive bias as a node embedding into the vector field while generalizing the notion of NODEs to graphs. By evolving a latent space representation of the edge connections coupled with a latent state space of node features, Huang et al. (2021) proposed a method that allows modeling dynamic graph structures over time together with temporally varying node features. Hereby a GNN is used to compute the latent initial states for edges and nodes, respectively, based on the observed sequence of node attributes and adjacency matrix sequences, whereby the temporal dimension is treated discretely via temporal edges. These states are then evolved via a coupled ODE to predict future nodes and edges, via the likelihood of the states. Choi et al. (2022) consider time series on a graph by using a graph embedding to capture the spatial dependencies from data, without directly incorporating prior graph knowledge for traffic forecasting, as the graph connection between nodes is learned not given. In (Jiang et al., 2023a) the initial latent representation

is first learned from initial observations at a point in time, then the continuous latent representation trajectory is learned as the solution to an ODE, which incorporates features as additional inputs via a GNN. Luo et al. (2023) use a graph with temporal edges to represent a time series and extract the initialization of latent states via graph convolution together with a spectral convolution, and evolve future node and edge representations using second-order ODEs. Qin et al. (2026) propose Graph Neural Controlled Differential Equationss (GN-CDEs), a method to learn a dynamic graph embedding by creating graph paths in the controlled differential equation, allowing for time dependent graph structures, rather then having a static graph, the whole graph control path over time has to be given. Berndt et al. (2026) introduce permutation equivariance into GN-CDEs. Chen et al. (2024) use two adaptive graph convolutions with opposite signs in their spatial architecture. Liu et al. (2025) give an overview of graphs and GNNs in NDEs.

2.4 Graphs as approximations of spatial continuum

Continuous methods exist that can be seen as a continuous version of GNNs, but they do not treat time series: Xhonneux et al. (2020) continuously diffuse along the spatial graph structure. GRAND (Chamberlain et al., 2021) is a method that treats a GNN as a discretization of an underlying diffusion process. CGNN (Xhonneux et al., 2020) generalize GNNs by seeing them as a specific discretization scheme. Continuous Graph Flow (Deng et al., 2019) are Ordinary Differential Equations (ODEs) that operate on a graph structure and Cranmer et al. (2020) distill symbolic representations of a learned deep model by introducing strong inductive bias via a GNN.

2.5 Simulations, applications, and other spatial information strategies

Chapman & Mesbahi (2011) formulated advection on graphs, Zang & Wang (2020) simulate network dynamics based on heat diffusion, mutualistic interaction of species and gene regulatory dynamics, and Arndt et al. (2025) use Partial Differential Equations (PDEs) to generate synthetic data for spatio-temporal graph forecasting. All three do not consider advection along graph edges. Maddix et al. (2022) describe a similar simulation to ours, with continuous time evolution at the nodes, but do not consider a continuous edge domain between nodes. Kirschstein & Sun (2024) investigate graph topology information for GNNs on a river discharge problem. Kratzert et al. (2018) forecast rainfall runoffs using LSTMs, however use additional weather data as features and predict gauge-wise, different to our setting. Jiang et al. (2023b) and Liu & Zhang (2024) give an overview of GNN for traffic forecasting. Apart from the discrete-time methods for traffic forecasting (Fang et al., 2021; Liu et al., 2023; Li et al., 2018; Lan et al., 2022; Xiao et al., 2025; Wu et al., 2019; Yu & Koltun, 2016; Yu et al., 2018; Zheng et al., 2020; Zhu et al., 2021; Guo et al., 2019; Shao et al., 2022; Weng et al., 2023), continuous-time methods were also used for this domain (Poli et al., 2021; Choi et al., 2022; Choi & Park, 2023). Kosma et al. (2023) use NODEs for epidemic spreading on graphs and Verma et al. (2024) use NODEs for climate and weather forecasting on discretized continuous space. Other attempts of incorporating prior spatial knowledge into NN architecture include Physics Informed Neural Networks (PINNS) Raissi et al. (2019), which enforce a prior defined PDE but do not act on graphs, as they avail oneself of a discretized continuous description of the spatial domain.

3 Background

NDEs model the evolution of a hidden state as the solution to a differential equation parameterized by a NN (Chen et al., 2018; Kidger, 2021). By treating time as continuous, NDEs process irregularly sampled observations naturally and admit memory-efficient training. This section recapitulates NODEs and the variants of NDEs that INDEQS builds on: NCDEs and their graph-based extensions.

3.1 Neural Ordinary Differential Equations

NODEs Chen et al. (2018) are time-continuous models that describe the evolution of a hidden state $y \in \mathbb{R}^{d_y}$ via a differential equation up to time $T > 0$

$$y(0) = y_0, \quad \frac{\mathrm{d}y(t)}{\mathrm{d}t} = f_\theta(t, y(t)), \quad t \in [0, T],$$

where the vector field on the right-hand side is a neural network $f_\theta : [0,T] \times \mathbb{R}^{d_y} \to \mathbb{R}^{d_y}$, with parameters θ — rendering the differential equation "neural". Lipschitz continuity of f_θ ensures the existence and uniqueness of a solution Kidger (2021). For some data input $x_0 \in \mathbb{R}^{d_x - 1}$ at time t_0, an affine mapping m_θ is applied to obtain the initial value for the differential equation $y_0 = m_\theta((t_0, x_0)) \in \mathbb{R}^{d_y}$, and thereby augmenting the NDE (Dupont et al., 2019). After evolving through virtual time up to T, the final state $y(T)$ serves as input to another affine layer l_θ to obtain the output of the model. NODEs can be considered the continuous-time limit of residual networks He et al. (2016) and can also be formulated in integral form via

$$y(0) = y_0, \quad y(T) = y(0) + \int_0^T f_\theta(s, y(s))\, \mathrm{d}s.$$

3.2 Neural Controlled Differential Equations

For modeling multivariate time series with observations $\{(t_i, x_i)\}_{i=0}^n$, one can turn to NCDEs (Kidger et al., 2020), which incorporate new observations continuously over time rather than only at initialization. To do so, the discrete observations are interpolated into a continuous path $x : [0,T] \to \mathbb{R}^{d_x}$ that acts as the control for the differential equation. An NCDE driven by x is then defined by

$$y(0) = y_0, \quad y(T) = y(0) + \int_0^T f_\theta(y(s))\, \mathrm{d}x(s),$$

with solution $y : [0,T] \to \mathbb{R}^{d_y}$, where $f_\theta : \mathbb{R}^{d_y} \to \mathbb{R}^{d_y \times d_x}$ is a neural network assumed to be Lipschitz continuous and the integral is taken in the Riemann–Stieltjes sense against the control path x, wherein the integrand $f_\theta(y(t))\, \mathrm{d}x(t)$ is a matrix-vector product. This control path x allows a continuous information inflow from data across $[0,T]$, in contrast to the NODE setting, where information enters only at $t = 0$. NCDEs can be considered operators that map from path space to path space. The initial state y_0 is obtained via a learnable function $n_\gamma : \mathbb{R}^{d_x} \to \mathbb{R}^{d_y}, x(0) \mapsto n_\gamma(x(0)) = y_0$. Due to the recurrent nature, NCDEs can be viewed as the continuous version of RNNs. The output is obtained through application of an affine layer l_θ via $o_t = l_\theta(y_t)$. For a differentiable path of bounded variation, reduction of the NCDE to an NODE is possible to attain

$$y(0) = y_0, \quad y(T) = y(0) + \int_0^T f_\theta(y(s)) \frac{\mathrm{d}x(s)}{\mathrm{d}s}\, \mathrm{d}s,$$

which allows the use of the training techniques of NODEs, with the integral now being a Riemann integral and the integrand $f_\theta(y(t)) \frac{\mathrm{d}x(t)}{\mathrm{d}t}$ again refering to a matrix-vector product.

3.3 Graph Neural Controlled Differential Equations

We write in the following $\{\mathcal{G}_{t_i} \triangleq (\mathcal{V}, \mathcal{E}, \mathbf{Y_{t_i}})\}_{i=0}^n$ for a multivariate time series $\mathbf{Y_{t_0}}, \ldots, \mathbf{Y_{t_n}} \in \mathbb{R}^{d_y}$ observed at times $t_0, \ldots, t_n$ on a directed graph $\mathcal{G}$ with vertices $v \in \mathcal{V}$ and edges $e \in \mathcal{E}$. To model this setting, Choi et al. (2022) rewrite the states of NCDEs to matrices in order to represent the additional graph dimensionality $|\mathcal{V}|$ by (see appendix A.2 for dimensional details)

$$\boldsymbol{H}(T) = \boldsymbol{H}(0) + \int_0^T f_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big) \frac{d\boldsymbol{X}(t)}{dt} dt, \tag{1}$$

wherein for all nodes, a d_h-dimensional hidden state $\boldsymbol{H}(t) \in \mathbb{R}^{|\mathcal{V}| \times d_h}$ is continuously updated in time, starting from $\boldsymbol{H}(0) = \boldsymbol{H}_0 \in \mathbb{R}^{|\mathcal{V}| \times d_h}$, $\boldsymbol{X}(t) \in \mathbb{R}^{|\mathcal{V}| \times d_x}$ is the control on the graph with dimensionality d_x for every node and $\boldsymbol{f_\theta} : \mathbb{R}^{|\mathcal{V}| \times d_h} \to \mathbb{R}^{|\mathcal{V}| \times d_h} \times \mathbb{R}^{|\mathcal{V}| \times d_x}$ the guiding vector field. Jhin et al. (2024) and Kidger (2021, p. 66) show that NCDEs can be coupled to use the encoded hidden path $\boldsymbol{H}$ as a control for a second NCDE with hidden state $\boldsymbol{Z}(t) \in \mathbb{R}^{|\mathcal{V}| \times d_z}$, with d_z being the dimensionality of $\boldsymbol{Z}$, which reduces to the NODE

$$\boldsymbol{Z}(T) = \boldsymbol{Z}(0) + \int_0^T \boldsymbol{g_\gamma}\Big(\boldsymbol{Z}(t)\Big) \frac{d\boldsymbol{H}(t)}{dt} dt, \tag{2}$$

with initial value $\boldsymbol{Z}(0) = \boldsymbol{Z}_0 \in \mathbb{R}^{|\mathcal{V}| \times d_z}$ and vector field $\boldsymbol{g_\gamma} : \mathbb{R}^{|\mathcal{V}| \times d_z} \to \mathbb{R}^{|\mathcal{V}| \times d_z} \times \mathbb{R}^{|\mathcal{V}| \times d_h}$. The coupled NODE describing the dynamics takes the form (intermediary steps can be found in A.3)

$$\frac{d}{dt} \begin{bmatrix} \boldsymbol{Z}(t) \\ \boldsymbol{H}(t) \end{bmatrix} = \begin{bmatrix} \boldsymbol{g_\gamma}\Big(\boldsymbol{Z}(t)\Big) \boldsymbol{f_\theta}\Big(\boldsymbol{H}(t)\Big) \frac{d\boldsymbol{X}(t)}{dt} \\ \boldsymbol{f_\theta}\Big(\boldsymbol{H}(t)\Big) \frac{d\boldsymbol{X}(t)}{dt} \end{bmatrix}. \tag{3}$$

One now constrains $\boldsymbol{f_\theta}$ to process information for every node separately to only capture the temporal dependencies individually, without mixing information across nodes, whereas $\boldsymbol{g_\gamma}$ learns the spatial dependencies.

For forecasting, the final state $\boldsymbol{Z}(T)$ encodes the information gathered from time 0 up to T and is used as input to a final convolutional layer to make the final predictions $\{\hat{\mathbf{Y}}_{t_i}\}_{i=0}^{n}$ with $T < t_i \leq T + \tau$ at time T for the next M time steps up to time $T + \tau$. One can solve and backpropagate through the NCDE given a loss function $\mathcal{L}(\{\hat{\mathbf{Y}}_{t_i}\}_{i=0}^{n}, \{\mathbf{Y}_{t_i}\}_{i=0}^{n})$ and optimize the parameters $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$.

4 Informed Graph Neural Controlled Differential Equations (INDEQS)

We present Informed Neural controlled Differential EQuationS (INDEQS) to incorporate prior directed graph structure into NCDEs, which act as an encoder of the features in the context window. We define two variations of INDEQS: inner and outer informedness. To highlight the differences in graph informing positions within the architecture of an NCDE, we distinguish between the inner mapping

$$\boldsymbol{g_\gamma}(\mathbf{Z}(t)) : \mathbb{R}^{d_{\boldsymbol{Z}}} \to \mathbb{R}^{d_{\boldsymbol{Z}}} \times \mathbb{R}^{d_{\boldsymbol{H}}} \tag{4}$$

and the outer mapping

$$\boldsymbol{g_\gamma}(\mathbf{Z}(t)) \bullet \cdot : \mathbb{R}^{d_{\boldsymbol{H}}} \to \mathbb{R}^{d_{\boldsymbol{Z}}}, \tag{5}$$

that the vector field $g_{\boldsymbol{\gamma}}$ in Equation (2) describes, using $\bullet$ to emphasize the tensor product, where $d_{\boldsymbol{Z}} = |\mathcal{V}| \times d_z$ and $d_{\boldsymbol{H}} = |\mathcal{V}| \times d_h$. Whereas Equation (4) describes the inner workings of the update of the hidden state $\mathbf{Z}$ on itself, the control, the tensor multiplication in Equation (5) describes the direct connection between control (and thereby the data) to the hidden state. Naturally, both happens simultaneously. The function in Equation (4) describes how a hidden state entry at a node has to encode "where to look" based on the entries of other hidden states and itself, to then "find" the information in the control. In contrast, the function in Equation (5) describes the situation in which one "knows where to look" (at least spatially) to read out the right hidden state update information from the control which is given. Figure 2 schematically illustrates the differences in the connections.

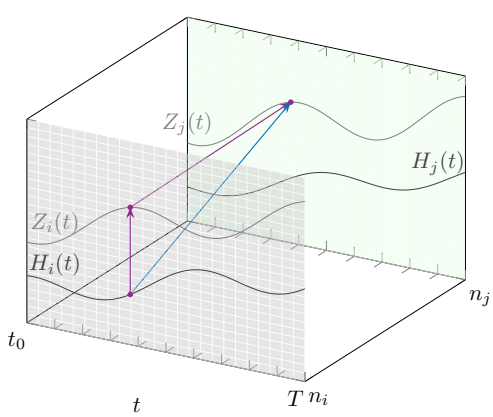


Figure 2: Difference in information transport between hidden state $\mathbf{H}_i$ at node n_i and hidden state $\mathbf{Z}_j$ at node n_j, occurring at every point in time t. Connection with $A_{\mathcal{V}}^{outer}$ (blue) leads to a direct connection versus connecting nodes via $A_{\mathcal{V}}^{inner}$ (violet).

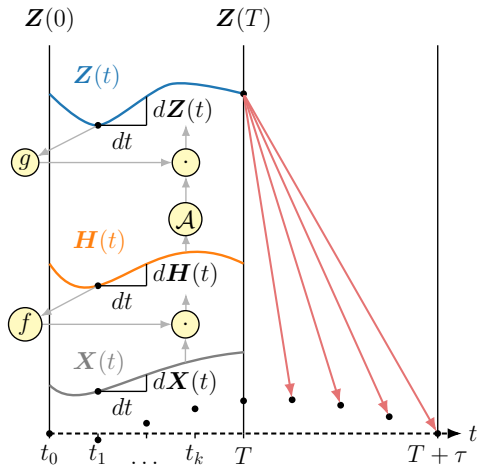


Figure 3: NCDE encoder and convolutional decoder. **Encoding** (left half): Up to time T, the data points at the bottom are interpolated to obtain a continuous path $\boldsymbol{X}$, whose derivative is then multiplied with f, to obtain $d\boldsymbol{H}$. $\mathcal{A}$ allows now direct mixing – at the *outer* position – of the nodes' control $d\boldsymbol{H}$, depending on $d\boldsymbol{H}$. Only after occurs the multiplication with g to obtain the final update $d\boldsymbol{Z}$. A mixing at the *inner* position within g can only be dependent on $\boldsymbol{Z}$. Multiplication here means tensor multiplication, and the 1-dimensionally depicted data and the paths, are multidimensional with multiple nodes and multiple dimensions per node. **Decoding** (right half): Based on the last hidden state $\boldsymbol{Z}(T)$, the convolution head (red arrows) directly makes all future prediction at only at predefined times.

4.1 Outer informed with inner node embedding: INDEQS$_{\text{outer}}$

To define *INDEQS*$_{outer}$, we use the prior known transposed vertex transition matrix $\boldsymbol{A}_{\mathcal{V}}^{outer}$ to inform our NCDE at the outer postion via

$$\boldsymbol{Z}(T) = \boldsymbol{Z}(0) + \int_0^T \boldsymbol{g}_{\boldsymbol{\gamma}}\Big(\boldsymbol{Z}(t)\Big)\mathbf{A}_{\mathcal{V}}^{outer}\frac{d\boldsymbol{H}(t)}{dt}dt, \tag{6}$$

where "outer" is referring to the position of the transposed node adjacency matrix. The internal mapping is given by

$$\boldsymbol{g}_{\boldsymbol{\gamma}}(\boldsymbol{Z}(t)) = g_3 \circ g_2 \circ g_1(\boldsymbol{Z}(t)),$$

with $g_1 : \mathbb{R}^{d_{\boldsymbol{Z}}} \to \mathbb{R}^{d_{\boldsymbol{Z}}}$, $g_3 : \mathbb{R}^{d_{\boldsymbol{Z}}} \to \mathbb{R}^{d_{\boldsymbol{Z}} \times d_{\boldsymbol{H}}}$ being fully connected layers with ReLU and hyperbolic tangent activation. INDEQS$_{\text{outer}}$ follows the parameterization of the inner g_2 via

$$g_2(B) = (\boldsymbol{I} + \phi(\sigma(\boldsymbol{E} \cdot \boldsymbol{E}^T)))BW, \tag{7}$$

as proposed in Choi et al. (2022), where $W \in \mathbb{R}^{d_{\boldsymbol{Z}}} \times \mathbb{R}^{d_{\boldsymbol{Z}}}$ is a trainable weight transformation matrix, that reweighs each nodes's high dimensional representation the same way, $\boldsymbol{E} \in \mathbb{R}^{|\mathcal{V}| \times C}$ is a learnable node embedding with embedding dimension $C \in \mathbb{N}$, ϕ is a row wise softmax activation and σ is meant to represent elementwise ReLU. Equation (7) is a graph convolutional operation Kipf & Welling (2017) with an adaptive, learnable adjacency matrix. Setting $\boldsymbol{A}_{\mathcal{V}}^{outer}$ to the identity fully recovers the setting of Choi et al. (2022). Throughout our experiments, this setting serves as the baseline, which we denote as *STG-NCDE*, following Choi et al. (2022).

4.2 Inner informed with outer identity: $\text{INDEQS}_{\text{inner}}$

To define $INDEQS_{inner}$ we set $\boldsymbol{A}_{\mathcal{V}}^{outer}$ to the identity matrix but replace the node embedding in Equation (7) with

$$g_2(B) = (\boldsymbol{A}_{\mathcal{V}}^{inner})B,$$

directly incorporating the transposed vertex transition matrix $\boldsymbol{A}_{\mathcal{V}}^{inner}$ at the inner position of the internal mapping. $\text{INDEQS}_{\text{inner}}$ has fewer parameters than STG-NCDE and $\text{INDEQS}_{\text{outer}}$, as the adjacency matrix is hardcoded without any learnable parameters, replacing the node embedding.

$\text{INDEQS}_{\text{inner}}$ constrains the flow of information to allow only communication between nodes which are connected via the adjacency matrix. This way one can make sure, that causally unrelated nodes are not allowed to communicate directly. For $\text{INDEQS}_{\text{outer}}$ the model has graph structure information, but is not constrained, as the model still is able to learn other patterns apart from the given adjacency connections. In the setting of STG-NCDE, one allows connections between all nodes and these connections are learned. In addition, we would like to point out that the configuration with both the outer and inner mechanisms set to an identity matrix, would keep each node information completely separate from each other, only processing the nodes' own state temporally, which would be equal to having $n-$many $1-$node models processed separately. The outer position of INDEQS can be seen analogous to a shortcut connection in a Residual Neural Network (ResNet) He et al. (2016), only between spatial nodes and not in the virtual time dimension.

The encoding is visually depicted in Figure 3, illustrating the different information positions with $\mathcal{A}$ at the outer position and g containing the inner graph connectivity position.

4.3 Higher order adjacencies

A predecessor of node m is a node n such that there exists a directed edge from n to m. In pursuit of integrating information from the predecessors of predecessors and higher degrees into our NCDEs, we replace $\boldsymbol{A}_{\mathcal{V}}$ in $\text{INDEQS}_{\text{outer}}$ and $\text{INDEQS}_{\text{inner}}$ by the sum over the k-th power adjacency matrices

$$\boldsymbol{A}_{\mathcal{V}}(k) = \sum_{i=0}^{k} \boldsymbol{A}_{\mathcal{V}}^{i}, \tag{8}$$

where k can be any integer less than or equal to the longest possible path length in the given directed graph. When informing our NCDE with adjacencies up to the l-th power via Equation (8), we refer to this configuration as $\text{INDEQS}_{\text{outer}}(k = l)$.

4.4 Continuous decoders

Instead of predicting future time steps with the default convolutional decoder, one can also continuously evolve the hidden states to be able to obtain predictions at continuous times via NODE based decoders that we outline in the appendix Section A.7.

5 Simulating Advection on Graph Edges

Continuous advection on a graph is most easily understood by following pulses as they travel along edges, fork at nodes according to predefined split ratios, and merge additively where multiple edges meet. One exemplary Gaussian pulse being advected on a 4-node graph is depicted in Figure 4. In the following, we present the mathematical details behind the simulation of advection on graph edges.

For a controlled experimental setting, we propose a simulation for linear advection along graph edges. In contrast to Chapman & Mesbahi (2011), where the quantities on the vertices are updated discretely in time, we advect quantities that move continuously in time along the edges of a graph and fork or merge at vertices. For the advection simulation, we consider a directed graph $\mathcal{G}$ with a set of vertices $\mathcal{V}$ and edges $\mathcal{E}$. Every edge $e \in \mathcal{E}$ has a time-static continuous domain $\Omega_e = \{x \in \mathbb{R} \mid 0 \leq x < \delta(e)\}$ and a function space $V_e = \{y_e(x, t)$

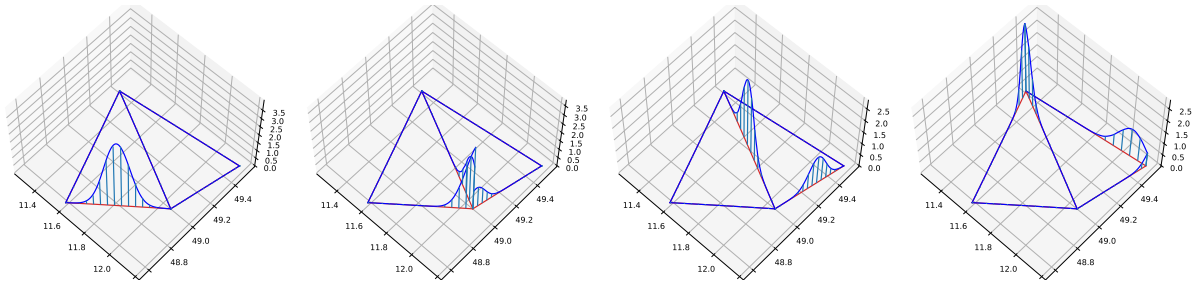


Figure 4: Advection of an initial Gaussian pulse on a 4 node graph with 5 edges over time

$\mid \Omega(e) \times \mathcal{T} \to \mathbb{R}^d\}$ attached to it, where $\delta(e)$ is the length of edge e and $t \in \mathcal{T} = [0, T]$ is a point in time. We first focus on the description of the advection on the interior of the edges without considering transitions between edges: Given an initial state of the dynamic system it evolves according to an advection differential equation

$$\frac{\partial \mathbf{y}}{\partial t} + \nabla \cdot (\mathbf{y} \odot \mathbf{v}) = 0, \quad \mathbf{y}(\,\cdot\,, 0) = \mathbf{y}_0 \tag{9}$$

with $\mathbf{v} = (v_1, \ \ldots, \ v_{|\mathcal{E}|})^\intercal$ being the vector of scalar velocity fields $v_e : \Omega_e \to \mathbb{R}$, with $e \in \{1, \ldots, |\mathcal{E}|\}$, that advect the quantity $\mathbf{y} = (y_{e_1}, \ \ldots, \ y_{e_{|\mathcal{E}|}})^\intercal$ through space over time. The divergence is intended row-wise and $\odot$ signifies element-wise multiplication. We restrict the entries of $\mathbf{y}$ to positive values, so that the flow direction is always the direction of the directed edge. We assume that the velocity field is constant. In the case of a one-dimensional quantity and velocity field along the edges, this leads to $\frac{\partial y_e}{\partial t} = -v_e \frac{\partial y_e}{\partial x}$, which has the analytical solution $y_e(x, t) = y_e^0(x - vt)$, with initial condition $y_e^0 := y_e(x, 0)$, for all $x \in \Omega(e)$, for all $e \in \mathcal{E}$ and $v_e t \leq x \leq \delta(e)$. With this description of the dynamic, y_e for $e \in \mathcal{E}$ is not required to be differentiable. Now, we describe the dynamic on the transition between adjacent edges. For $x < v_e t$ one would look back "beyond the edge".

We therefore resort to a matrix formulation to represent the edge transitions of y:

$$\mathbf{y}(\mathbf{x}, t) = \big(\mathbf{A}_\mathcal{E} \mathbf{y}(\mathbf{x}, 0)\big)\Big|_{\mathbf{x} = (\delta(\mathbf{e}) - v_e t \ \mathbf{1}_{|\mathcal{E}|})}, \quad x < v_e t, \tag{10}$$

where $t < \min_{e \in \mathcal{E}} \delta(e)/v_e$ has to hold for every edge to not look further back than the previous edge and where $\mathbf{A}_\mathcal{E}$ is a directed edge transition matrix, signifying to which edge a quantity transitions when the quantity reaches the end of an edge. $\mathbf{A}_\mathcal{E}$ acts as a function operator on the vector of functions $\mathbf{y}_0 = (y_1^0, \ \ldots, \ y_{|\mathcal{E}|}^0)^\intercal$, and $\mathbf{x} = (x_1, \ \ldots, \ x_{|\mathcal{E}|})^\intercal$ is a collection vector of spatial coordinates on the different edges and $\mathbf{1} = (1, \ \ldots, \ 1)^\intercal \in \mathbb{R}^{|\mathcal{E}|}$. The entries a_{ij} of $\mathbf{A}_\mathcal{E}$ are defined as

$$a_{ij} = \begin{cases} p_{ij} \in (0, 1], & \text{if } e_i \text{ follows on } e_j \\ 0, & \text{else} \end{cases},$$

with p_{ij} being the proportion of the quantity on e_i transported to e_j and $\sum_{i \in \mathcal{E}} p_{ij} = 1$ to enforce conservation. The matrix $\mathbf{A}_\mathcal{E}$ can be obtained from the the vertex adjacency matrix $\mathbf{A}_\mathcal{V}$ (details in A.4). We then iteratively advect with a recurrence equation derived from Equation (10) to derive

$$\mathbf{y}(\mathbf{x}, t + \Delta t) = \big(\mathbf{A}_\mathcal{E}(\mathbf{y}(\mathbf{x}, t))\big)\Big|_{\mathbf{x} = (\delta(\mathbf{e}) - v \Delta t \ \mathbf{1}_{|\mathcal{E}|})},$$

which can be used for simulating data.

6 Experiments

We begin by describing the generation of the simulated data, followed by the description of the river discharge dataset and the traffic flow forecating dataset.

6.1 Description of datasets

6.1.1 Advection simulation data

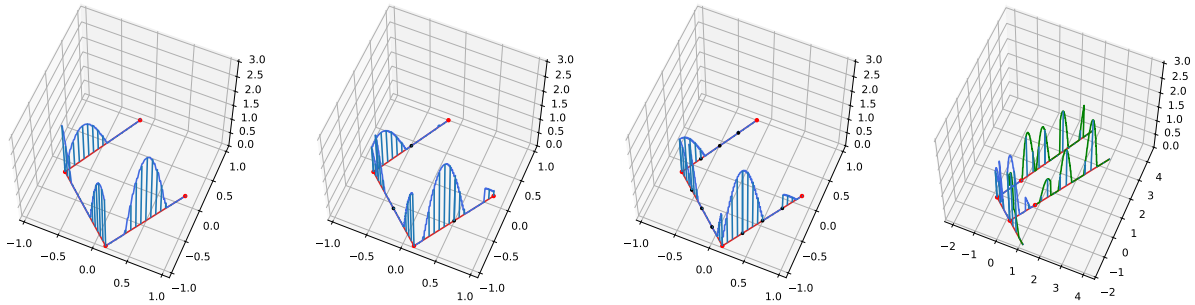


Figure 5: Advection on graph edges for a 4-node graph for 3 time steps and increasing node resolution. The additional intermediate nodes are depicted as black dots. The last image additionally shows a zoomed out view of another time step with future masses along the virtual edges (green) where masses enter at the top right edges and leave the graph on the bottom edge.

For the experiments on graph advection data, we first randomly sample graphs with number of nodes being $4, 8, 16, 32$,64 and 128, respectively, and hold these constant for the advection simulation along the edges. The (directed) graphs represent randomly generated Growing Network with Redirection (GNR) graphs (Krapivsky & Redner, 2001) (see A.5 for details), resembling the graph structure of a river network

$$y_0(x) = \max\Big(0, a_0 + \sum_{k=1}^{K} a_k \cos(2\pi kx/L) + b_k \sin(2\pi kx/L)\Big), \tag{11}$$

where K is a small random positive integer uniformly drawn from $\{2,\ldots, 20\}$, $a_0 = 0.2$, and the coefficients a_k, b_k are independent Gaussian variables with decaying variance $k^{-\alpha}$ with $\alpha = 5$ (i.e. higher modes are damped), so that each edge carries a smooth, spatially correlated random profile with most power in low spatial frequencies.

We simulate the advection dynamic along the edges 2000 times with different initial conditions, for each of the graphs, and use $\Delta t = 8$ minutes to evolve for 24 steps into the future. To have enough mass influx into the graph system for future steps, virtual edges are initialized accordingly (see Figure 5). To obtain data measurements at the nodes, the quantity that passed through the vertices in a given time span is aggregated. We take measurements at the nodes for $\Delta t = 8$ and acquire time series on the graph nodes $\{\mathcal{G}_{t_i} \triangleq (\mathcal{V}, \mathcal{E}, \mathbf{Y_{t_i}})\}_{i=0}^{n}$ that are used for training. The edges are of length 64 and the quantities move at speed $v = 1$. The task is to predict the quantities for the next 12 time points given the previous 12 time points, such that the previous nodes provide enough information to be able to infer the quantities at the subsequent nodes, which renders an adjacency matrix power of 1 the reasonable choice. We train on 80% of the data, use 10 % for validation and 10 % as a holdout test set. We train, validate and test on the non-source nodes, i.e. the nodes that have preceding nodes with measurements that would allow perfect prediction. For testing the stability of the methods for different spatial node resolutions k, we divide each edge into k intervals, leading to $k - 1$ additional intermediate nodes, where additional measurements are taken. The graph adjacency matrix is rewired to reflect these additional nodes. Apart from the resolution, the graph structure, the initialization and the advective behavior stay the same. The different node resolutions are depicted in Figure 5. The code of the simulation and the generated data can be found in the code repository (`https://anonymous.4open.science/r/indeqs_tmlr-588E`).

6.1.2 River discharge data

In our real-world data experiments, we use runoff data from "The Global Runoff Data Centre, 56068 Koblenz, Germany". It includes daily measurements of mean discharges of the river Weser, recorded starting 1 Jul

1820 up till 25 Jul 2023 for at least one station. We selected the time span from January 6, 1998, to October 31, 2016 (6874 days), as it provided the longest possible overlapping period during which measurements were available for all stations. We excluded two stations because they contained no information on connected stations. The unit of measure for the discharge data is cubic meters per second (m^3/s). This dataset provides valuable insights into the hydrological dynamics of the Weser River over an extended period. The dataset for the experiments features 45 nodes and 44 edges. We selected the Weser River network, as this river basin has a comparable size to our simulation experiments and provides information of the next downstream stations, allowing to create an adjacency matrix for informedness. The data can be found in the code repository. The task is to predict future discharges of the next 5 days given a context of the last 7 days, leading to 572 complete, disjoint time series fragments. For the training, we use a chronological 80/10/10 split for training, validation and test set, respectively. We use a stride of 1 to augment the number of samples to obtain 5489, 676 and 676 samples for training, validation and test set.

6.1.3 Traffic flow data

The PeMS08 dataset comprises district 8 of the the Caltrans Performance Measurement System (PeMS). It captures traffic flow measurements across the California highway system at a frequency of 5 minutes (288 measurements per day), spanning from 01 Jan 2016 to 31 Aug 2016. The monitored network consists of 170 nodes and 295 edges, providing a detailed representation of the sensor network in the San Bernardino area. To leverage the spatial dependencies, we construct an informed adjacency matrix $A \in \mathbb{R}^{N \times N}$ using a thresholded Gaussian kernel (Shuman et al., 2013) based on the physical distances $d_{i,j}$ between sensors:

$$w_{i,j} = \exp\left(-\frac{d_{i,j}^2}{\sigma^2}\right) \tag{12}$$

where σ is the standard deviation of all recorded distances. We apply a threshold $r = 0.01$ such that $A_{i,j} = w_{i,j}$ if $w_{i,j} \geq r$, and 0 otherwise. This high-resolution temporal data enables in-depth studies of traffic fluctuations and dynamics within the network. Similar to the hydrological experiments, the task is to predict future traffic flow of the next hour given a context of the last hour, leading to 445 complete, disjoint time series fragments. For the training, we use a chronological 60/20/20 split for training, validation and test set, respectively. We use a stride of 1 to augment the number of samples to obtain 14,271, 1,784, and 1,784 samples, respectively, allowing for a precise analysis of the traffic patterns over the monitored period.

6.2 Results

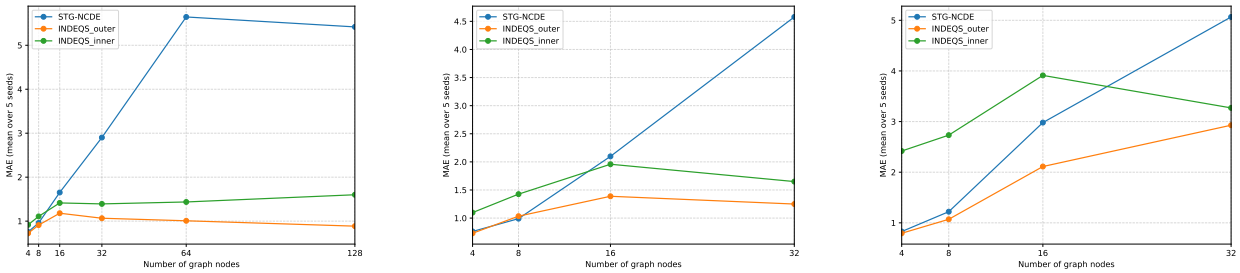
We demonstrate the performance of INDEQS on the advection simulation data and a river discharge forecasting tasks on a river network while only using the endogenous discharges and no exogenous features, as the natural phenomenon of water flow exhibits an advective behavior, conserving masses moving steadily over time and we observe benefits of graph information for our advection simulation data. We also expect the river flows to behave conservatively to a degree and be more predictable than tasks solely involving human-interactions like traffic flow forecasting, which we will also study as the final task.

To train INDEQS we use hermite cubic splines with backward differences (Morrill et al., 2021) to construct differentiable paths $\mathbf{X}(t)$ from the given data points and *RK4*, a 4th order Runge-Kutta method (Runge, 1895; Kutta, 1901) to solve the differential equations. We train for 200 epochs for the advection simulation experiments, the river discharge and traffic flow problem and select the model that attained the best validation loss over the whole training period. For the simulation data, the discharge and traffic flow predictions, we train INDEQS in both variations and STG-NCDE with 5 random seeds.

6.2.1 Advection Experiment

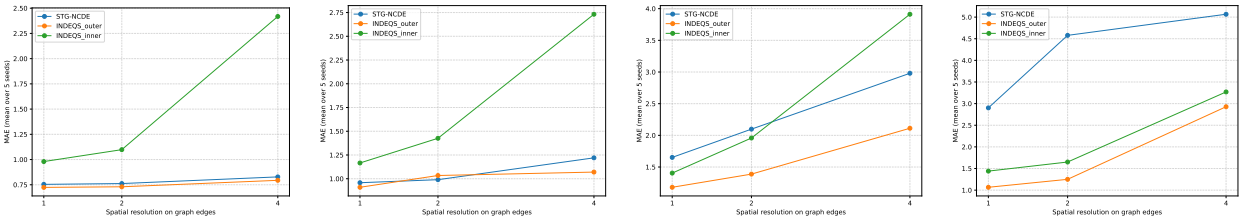
For the advection simulation experiment, we compare graph informed $\text{INDEQS}_{\text{outer}}$ and $\text{INDEQS}_{\text{inner}}$ to STG-NCDE. We observe in Figure 6 that the informed $\text{INDEQS}_{\text{outer}}$ (orange) is attaining a lower MAE compared to the uninformed STG-NCDE (blue) method for all graph sizes for spatial node resolution of 1 (see Figure 6 (a)) and 4 (see Figure 6 (c)), and also having lower MAE for spatial node resolution 2 for all

considered graph sizes, except for a graph of size 8, where the performance is almost on par (see Figure 6 (b)). For a spatial resolution of 1 and 2, $\text{INDEQS}_{\text{outer}}$ exhibits a relatively stable MAE level over the node numbers, while the MAE of STG-NCDE is increasing with increasing graph sizes and then plateauing for 64 nodes and 128 nodes. For spatial resolution of 2, STG-NCDE exhibits increasing MAE for higher node numbers, a pattern observed also for spatial resolution of 4. $\text{INDEQS}_{\text{inner}}$ (green) has higher MAE than STG-NCDE for low node numbers, however exhibits lower MAE than STG-NCDE starting for higher node numbers. The turning point of this behavior increases with spatial resolution. All methods degenerate with increasing spatial resolution, while $\text{INDEQS}_{\text{inner}}$'s MAE increases most sharply for the 4-,8- and 16-node compared to $\text{INDEQS}_{\text{outer}}$ (see Figure 7). The results suggest that $\text{INDEQS}_{\text{outer}}$ is more stable across graph size and spatial resolution. All results are also provided in Table 4.



(a) Spatial node resolution = 1 (b) Spatial node resolution = 2 (c) Spatial node resolution = 4

Figure 6: MAE over 5 seed runs over graphs with increasing number of nodes for the **Advection Experiment** with fixed spatial node resolution.



(a) 4-node graph (b) 8-node graph (c) 16-node graph (d) 32-node graph

Figure 7: Mean MAE over 5 runs for increasing spatial node resolution for the **Advection experiment** with fixed graph size.

6.2.2 River discharges

For the river discharge experiment, we compare INDEQS to the uninformed STG-NCDE (Choi et al., 2022) and the continuous graph informed Graph Convolutional ODE with Gated Recurrent Units (GCDE-GRU) (Poli et al., 2021). To contextualize the performance of our continuous model, we include comparisons with informed discrete-time recurrent model DCRNN Li et al. (2018), and informed discrete-time convolution-based GWaveNet (Wu et al., 2019).

We consider for this task higher adjacency matrix powers and different decoders for the INDEQS methods. The results versus other methods on the water discharge task can be found in Table 1. $\text{INDEQS}_{\text{outer}}$ has an MAE of 5.34 compared to uninformed STG-NCDE with MAE of 5.59. We further investigate the forecasting performance for matrix adjacency powers from $k = 1$ up to $k = 12$, the maximum steps one can take upstream, in the water discharge graph. Higher adjacency matrix powers lead to lower MAE for $\text{INDEQS}_{\text{inner}}$ and to a smaller degree also for $\text{INDEQS}_{\text{outer}}$ (see Figure 8), attaining MAEs of 5.34 and 5.20, respectively, for an adjacency matrix power of 12. $\text{INDEQS}_{\text{outer}}$ incurs only marginal overhead in VRAM and compute time, while $\text{INDEQS}_{\text{inner}}$ slightly reduces VRAM use and trains 24% faster than STG-NCDE , owing to the lower parameter count of the Adaptive Graph Convolution (AGC). The continuous NODE_g

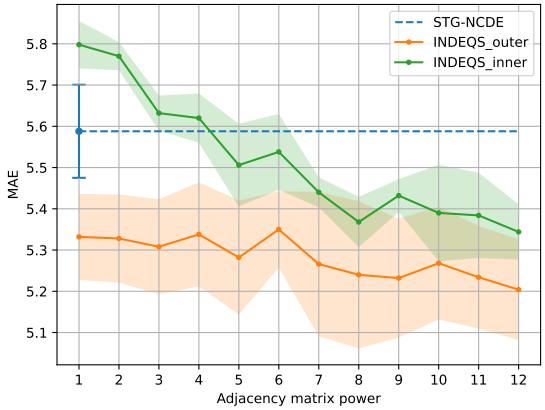


Figure 8: Average performance of INDEQS with increasing adjacency matrix powers vs. the uninformed STG-NCDE for the task of **water discharges** over 5 runs, showing a trend for increased performance for higher adjacencies.

and NODE_{ctrl} decoders lead to additional MAE performance gains for an informed $\text{INDEQS}_{\text{outer}}$, improving the MAE of the convolutional decoder of 5.20 to 5.07 and 5.01, respectively — surpassing the uninformed STG-NCDE baseline and the additionally considered informed NODE baseline GCDE-GRU. In Table 1 we further compare to discrete-time graph-informed methods and observe that $\text{INDEQS}_{\text{outer}}$ achieves a lower MAE compared to DCRNN but does not match GWaveNet, which achieves the best MAE on the task of water discharges.

Table 1: Comparison of INDEQS vs. the uninformed STG-NCDE and other baselines regarding quantitative performance in terms of averaged MAE and RMSE over five runs in the task of **water discharges** prediction.

Water discharges	**Performance and model specs.**					**Model type**
	MAE ↓	RMSE ↓	#Params.	Time (Epoch/Total)	VRAM	
DCRNN Li et al. (2018)	5.09 ±0.03	16.66 ±0.18	**23,729**	13.8 s/ 38.4 min	117 MB	informed discrete-time RNN
GWaveNet Wu et al. (2019)	**4.95** ±0.13	**14.89** ±0.42	302,537	**3.6** s/ **5.93** min	1,808 MB	informed discrete-time CNN
GCDE-GRU Poli et al. (2021)	6.28 ±0.29	17.75 ±0.37	33,281	91.7 s/ 62 min	**74** MB	informed NODE
STG-NCDE Choi et al. (2022)	5.59 ±0.13	18.73 ±0.65	415,879	11.3 s/ 37.8 min	560 MB	uninformed NCDE
$\text{INDEQS}_{\text{NODE}_{ctrl}}$ (**ours**)	5.01 ±0.16	16.10 ±0.65	416,500	28.0 s / 93.2 min	902 MB	informed NCDE
$\text{INDEQS}_{\text{NODE}_g}$ (**ours**)	5.07 ±0.08	16.43 ±0.34	415,619	17.13 s / 57.1 min	833 MB	informed NCDE
$\text{INDEQS}_{\text{inner}}(k = 12)$ (**ours**)	5.34 ±0.07	17.73 ±0.64	291,909	8.5 s / 28.6 min	535 MB	informed NCDE
$\text{INDEQS}_{\text{outer}}(k = 12)$ (**ours**)	5.20 ±0.12	16.97 ±0.40	415,879	12.1 s / 40.2 min	573 MB	informed NCDE

Given the superior performance of $\text{INDEQS}_{\text{outer}}$ compared to $\text{INDEQS}_{\text{inner}}$, due to the additional data-adaptivity, we focus on the former for the following traffic forecasting task.

6.2.3 Traffic forecasting

For the PeMS08 traffic flow dataset, we compare $\text{INDEQS}_{\text{outer}}$ to STG-NCDE to demonstrate that the graph information also works for a task that is more influenced by human behavioral patterns and individual decisions, with a less clear causal graph structure. Additionally, the dataset is an established benchmark dataset in spatio-temporal graph forecasting.

We observe in Table 2 that $\text{INDEQS}_{\text{outer}}$ performs slightly better on the PeMS08 traffic flow dataset than the uninformed STG-NCDE model with a Mean Absolute Error (MAE) over 5 runs of 16.50 vs. 16.55 (see Table 2), demonstrating that the graph topology information is also useful for application domains that exhibit additional random behavior. The results are not directly comparable to the traffic flow forecasting literature, as we report the results over multiple seeds, while in the literature mostly only one seed result is

reported. By additionally optimizing for the best graph adjacency power, one even attains an MAE of 16.39 (see Table 3).

Table 2: Overview of MAE, number of parameters, training time and the epoch when validation loss last improved, with standard deviations, for uninformed STG-NCDE vs. informed $\text{INDEQS}_{\text{outer}}$ for the **PeMS08 traffic** prediction over 5 runs with different random seeds.

	Outer	**Inner**	**MAE (test)**	**#Params.**	**MAE (val.)**	**Train time**	**Last improvement**
STG-NCDE	Identity	AGC	16.55 ± 0.20	45,152	17.00 ± 0.22	129.31 min ± 1.04	183.00 ± 3.94
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	**16.50** ± 0.19	45,152	16.88 ± 0.28	143.18 min ± 1.45	169.00 ± 11.20

We find empirical evidence that $\text{INDEQS}_{\text{outer}}$ is preferred, when best performance is required and one wants to inform the model with a pre-defined graph structure in addition to having the adaptive graph convolutional component that is able to learn patterns apart from the pre-defined graph. Additional communication between non-connected nodes in the pre-defined graph is possible in this variant. The pre-defined graph structure is in this sense *informing*. In $\text{INDEQS}_{\text{inner}}$ on the other hand, the pre-defined graph structure is *constraining* the direct communication between nodes according to the pre-defined graph. This can be desired, if one is certain about the underlying process of the data and wants to hinder communication between unconnected nodes. We provide further experiments regarding continuous decoders, and an analysis of solvers and solver step sizes in Section A.9.3 and Section A.9.4, respectively.

7 Discussion

Our empirical study provides several insights into when and how graph-informed NCDE models are beneficial for spatio-temporal forecasting. Across the controlled advection simulations, the river discharge task, and the PeMS08 traffic forecasting benchmark, we consistently observe that incorporating prior knowledge about the underlying graph structure into the NCDE improves predictive performance over the uninformed baseline STG-NCDE, particularly when the graph encodes physically meaningful flow or connectivity patterns. $\text{INDEQS}_{\text{outer}}$ with convolutional decoder head is the overall best choice of the different INDEQS variants, if useful graph information is available. $\text{INDEQS}_{\text{inner}}$ is favorable if one wants to restrict the connectivity between graph nodes to the given graph adjacency matrix, leading to a lighter and faster model with only slightly worse performance than $\text{INDEQS}_{\text{outer}}$, due to not possesing the data adaptive capabilities of the AGC. For real world problems it is advantageous to use the continuous decoder setups, due to their higher expressivity. However they require more training than the convolutional decoder.

On the advection simulation data, $\text{INDEQS}_{\text{outer}}$ and $\text{INDEQS}_{\text{inner}}$ both benefit from access to the true adjacency matrix of the underlying dynamic. Informing the model at the outer position ($\text{INDEQS}_{\text{outer}}$) leads to robust gains and these increase up to a point, as the number of graph node increases. We suspect gains of the same magnitude for larger graphs. The inner variant ($\text{INDEQS}_{\text{inner}}$) exploits graph structure more aggressively through a constrained spatial vector field. The inner variant is performing worse than STG-NCDE for higher spatial resolution, but increasingly better for higher numbers of graph nodes. This suggests that for smaller graphs the AGC is compensating for the lacking graph structure and can learn it from data. As the graph becomes larger, the higher the importance of the underlying structure, which cannot be adequately be learned from the data as for smaller graphs. The experiments on varying node resolution

Table 3: MAE with standard deviation over 5 runs for different outer-inner graph configurations for increasing powers of the adjacency matrix for the **PeMS08 traffic** prediction.

	Adjacency matrix power				
	1	2	3	4	5
$\text{INDEQS}_{\text{outer}}$	16.50 ± 0.17	**16.39** ± 0.18	16.53 ± 0.13	16.53 ± 0.19	16.53 ± 0.12
STG-NCDE	16.55 ± 0.18	-	-	-	-

indicate that the proposed mechanisms remain effective to a certain degree when the graph is refined. The degrading performance in this case shows that the problem is becoming more difficult, as information now has to travel via multiple hops. The uninformed NCDE, however, is unable to learn the graph structure from the limited given amount of samples, even with clean signal data in the controlled advection simulation setting.

For the river discharge task, $\text{INDEQS}_{\text{inner}}$ achieves lower MAE than an uninformed NCDE with learnable graph embedding when the adjacency power is chosen appropriately. This highlights that constraining the propagation of information to physically plausible connections can be more beneficial than allowing arbitrary spatial long-range communication, especially in settings where mass conservation and directed flow are central. At the same time, $\text{INDEQS}_{\text{outer}}$ achieves competitive or better performance while adding only marginal overhead in terms of VRAM and compute time.

On the PeMS08 traffic forecasting benchmark, where the dynamics are influenced by additional unobserved factors and noise, the performance gap between informed and uninformed models is smaller. Nevertheless, $\text{INDEQS}_{\text{outer}}$ still slightly outperforms the uninformed STG-NCDE, indicating that real-world road network information remains useful even when the graph structure does not fully explain the observations. This suggests that INDEQS can serve as a flexible method that combines pre-defined topology with data-driven adjustments through the adaptive graph convolution component.

A second set of insights concerns the choice of decoder. In both the river discharge and traffic experiments, continuous-time decoders (NODE_g and NODE_{ctrl}) consistently outperform the discrete convolutional decoder in terms of validation and test MAE. This supports the view that continuous latent dynamics are a natural fit for NCDE-based models on graph time series, especially when predictions at arbitrary time points are of interest. However, these gains come at increased computational cost, most noticebly for NODE_{ctrl}, which requires solving an additional ODE for the learned control signal. In practice, NODE_g offers a favorable trade-off between accuracy, parameter count, and runtime. Surprisingly, the continuous decoders do not perform well on the advection simulation.

One obvious limitations is the requirement of knowing the underlying graph structure, which is not always obtainable. Also our evaluations only encompass limited graph types, graph sizes and domains. It is also difficult to distinguish true underlying graph structure of the dynamic from a mere spatial proximity graph structure, or to discern if a given graph structure is valuable.

Overall, our results indicate that graph-informed NCDEs are particularly beneficial when (i) a reliable graph describing flow or interaction structure is available, (ii) the forecasting horizon and spatial resolution require information to propagate over multiple hops, and (iii) continuous-time evolution of latent trajectories is advantageous. In such settings, $\text{INDEQS}_{\text{outer}}$ is a strong choice when performance and flexibility are prioritized, whereas $\text{INDEQS}_{\text{inner}}$ is appealing when one wishes to enforce strict adherence to a known topology. We believe that these findings encourage further exploration of informed neural differential equation models for spatio-temporal problems beyond the domains considered in this work.

8 Conclusion

We introduced INDEQS, a graph-informed Neural Controlled Differential Equation model that separates inner mixing of hidden states from outer mixing between vector field and control. By injecting prior knowledge of directed graph structure at these distinct positions, INDEQS can achieve lower forecasting errors than uninformed NCDE baselines with comparable parameter counts, particularly on larger graphs and tasks that require information to propagate over multiple hops. Through the introduced controlled advection simulations and real-world experiments on river discharge and traffic flow, we showed that outer informedness is a strong and flexible default, while inner informedness offers a more parameter-efficient alternative when strict adherence to a known adjacency is desired. Our results highlight the promise of combining neural differential equations with explicit spatial structure, and motivate further work on informed continuous-time models for further spatio-temporal applications.

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A Appendix

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A.1 List of Acronyms

Acronyms

AGC	Adaptive Graph Convolution
AST-GCN	Attribute-Augmented Spatiotemporal Graph Convolutional Network
ASTGCN	Attention Based Spatial-Temporal Graph Convolutional Networks
CDE	Controlled Differential Equation
DCRNN	Diffusion Convolutional Recurrent Neural Network
GCDE-GRU	Graph Convolutional ODE with Gated Recurrent Units
GCN	Graph Convolutional Networks
GMAN	Graph Multi-Attention Network
GN-CDE	Graph Neural Controlled Differential Equations
GNCDE	Graph Neural Controlled Differential Equation
GNN	Graph Neural Network
GNR	Growing Network with Redirection
GRU	Gated Recurrent Unit
GWaveNet	Graph WaveNet
LSTM	Long Short Term Memory
MAE	Mean Absolute Error
NCDE	Neural Controlled Differential Equation
NDE	Neural Differential Equation
NN	Neural Network
NODE	Neural Ordinary Differential Equation
ODE	Ordinary Differential Equation
PDE	Partial Differential Equation
ResNet	Residual Neural Network
RNN	Recurrent Neural Network
STG-NCDE	Spatial Temporal Graph Neura Controlled Differential Equations
STGCN	Spatial-Temporal Graph Convolutional Network
TCN	Temporal Convolutional Network

A.2 Dimensions

The dimensions of the domains and codomains of the vector field functions $f_{\boldsymbol{\theta}}$ and $g_{\boldsymbol{\gamma}}$ can be described even more precisely with

$$\boldsymbol{f}_{\boldsymbol{\theta}}(\cdot) : \mathbb{R}^{|\mathcal{V}| \times d_h} \to \mathbb{R}^{|\mathcal{V}| \times d_h} \times \mathbb{R}^{|\mathcal{V}| \times d_x}$$
$$\boldsymbol{g}_{\boldsymbol{\gamma}}(\cdot) : \mathbb{R}^{|\mathcal{V}| \times d_z} \to \mathbb{R}^{|\mathcal{V}| \times d_z} \times \mathbb{R}^{|\mathcal{V}| \times d_h}$$

and $\mathbf{H}(t) \in \mathbb{R}^{|\mathcal{V}| \times d_h}$, $\mathbf{Z}(t) \in \mathbb{R}^{|\mathcal{V}| \times d_z}$, $\mathbf{X}(t) \in \mathbb{R}^{|\mathcal{V}| \times d_x}$, with d_h, d_z and d_x being the dimensionality of the corresponding (hidden) states or control per vertex, leading to a description of the tensor product in Equation (1) with einstein notation while omitting the indices of $\boldsymbol{f}$ and $\boldsymbol{g}$ — $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ — for more clarity

$$\left(\frac{d\mathbf{H}}{dt}\right)_{mh} = \left(\boldsymbol{f}\frac{d\mathbf{X}}{dt}\right)_{mh} = \boldsymbol{f}_{mhnx}\left(\frac{d\mathbf{X}}{dt}\right)_{nx}$$

and for Equation (2)

$$\left(\frac{d\mathbf{Z}}{dt}\right)_{kz} = \left(\boldsymbol{g}\frac{d\mathbf{H}}{dt}\right)_{kz} = \boldsymbol{g}_{kzmh}\left(\frac{d\mathbf{H}}{dt}\right)_{mh}, \tag{13}$$

where n, m, and k are indices for the vertices, h and z are the indices for the dimension of hidden states $\mathbf{H}$ and $\mathbf{Z}$, respectively and x is the index for the dimension of the control path $\mathbf{X}$.

If one now wants to incorporate graph information at the outer position in Equation (6), one would insert $\mathbf{A}_{\mathcal{V}}$ into Equation (13) and obtain

$$\left(\frac{d\mathbf{Z}}{dt}\right)_{kz} = \left(\boldsymbol{g}\frac{d\mathbf{H}}{dt}\right)_{kz} = \boldsymbol{g}_{kzmh}\ \left(\mathbf{A}_{\mathcal{V}}\right)_{mn}\ \left(\frac{d\mathbf{H}}{dt}\right)_{nh}.$$

A.3 System of Differential Equations

Starting from the coupled differential equations

$$\begin{bmatrix} \boldsymbol{Z}(T) \\ \boldsymbol{H}(T) \end{bmatrix} = \begin{bmatrix} \boldsymbol{Z}(0) + \int_0^T \boldsymbol{g}_{\boldsymbol{\gamma}}\Big(\boldsymbol{Z}(t)\Big)\frac{d\boldsymbol{H}(t)}{dt} \\ \boldsymbol{H}(0) + \int_0^T \boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\boldsymbol{X}(t)}{dt} \end{bmatrix} \tag{14}$$

with

$$\begin{aligned} \frac{d\boldsymbol{H}(t)}{dt} &= \frac{d}{dt}\left(\mathbf{H}(0) + \int_0^t \boldsymbol{f}_\theta\Big(\mathbf{H}(s)\Big)\frac{d\mathbf{X}(s)}{ds}ds\right) \\ &= \frac{d}{dt}\left(\int \boldsymbol{f}_\theta\Big(\mathbf{H}(s)\Big)\frac{d\mathbf{X}(s)}{ds}ds\Bigg|_{s=t} - \int \boldsymbol{f}_\theta\Big(\mathbf{H}(s)\Big)\frac{d\mathbf{X}(s)}{ds}ds\Bigg|_{s=0}\right) \\ &= \boldsymbol{f}_\theta\left(\mathbf{H}(t)\right)\frac{d\mathbf{X}(t)}{dt}, \end{aligned} \tag{15}$$

it follows that

$$\begin{bmatrix} \boldsymbol{Z}(t) \\ \boldsymbol{H}(t) \end{bmatrix} = \begin{bmatrix} \boldsymbol{Z}(0) + \int_0^T \boldsymbol{g}_{\boldsymbol{\gamma}}\Big(\boldsymbol{Z}(t)\Big)\boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\boldsymbol{X}(t)}{dt} \\ \boldsymbol{H}(0) + \int_0^T \boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\boldsymbol{X}(t)}{dt} \end{bmatrix}. \tag{16}$$

Differentiating and using Equation (15) for $\boldsymbol{H}$ and analogously for $\boldsymbol{Z}$ gives

$$\frac{d}{dt}\begin{bmatrix} \boldsymbol{Z}(t) \\ \boldsymbol{H}(t) \end{bmatrix} = \begin{bmatrix} \boldsymbol{g}_{\boldsymbol{\gamma}}\Big(\boldsymbol{Z}(t)\Big)\boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\boldsymbol{X}(t)}{dt} \\ \boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\boldsymbol{X}(t)}{dt} \end{bmatrix}. \tag{17}$$

A.4 Edge transition matrix

To obtain the edge transition matrix $\mathbf{A}_{\mathcal{E}}$ from a weighted vertex adjacency matrix $\mathbf{A}_{\mathcal{E}}$ with $\sum_{j\in|\mathcal{E}|}(\mathbf{A}_{\mathcal{E}})_{ij} = 1$, one first starts off with the vertex incidence matrix $\mathbf{I}$. Let us define some matrix operations for $\mathbf{I} \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{E}|}$, namely

$$(\mathbf{I}^{+})_{ij} = \begin{cases} (\mathbf{I})_{ij}, & \text{if } (\mathbf{I})_{ij} > 0 \\ 0, & \text{else} \end{cases},$$

$$(\mathbf{I}^{-})_{ij} = \begin{cases} -(\mathbf{I})_{ij}, & \text{if } (\mathbf{I})_{ij} < 0 \\ 0, & \text{else} \end{cases},$$

$$(\mathbf{I}^{c})_{ij} = \begin{cases} 1, & \text{if } (\mathbf{I})_{ij} > 0 \\ (\mathbf{I})_{ij}, & \text{else} \end{cases},$$

thereby $(\cdot)^c$ is making $\mathbf{I}$ conservative. In total the edge transition matrix $\mathbf{I}_{\mathcal{E}}$ is given by

$$\mathbf{A}_{\mathcal{E}} = (\mathbf{I}^{-})^{\intercal}(\mathbf{I}^{c})^{+}.$$

On the one side $(\mathbf{I}^{-})^{\intercal} \in \mathbb{R}^{|\mathcal{E}|\times|\mathcal{V}|}$ considers the incoming magnitude of the transported quantities from edges to vertices and also the amount of quantities, on the other side $(\mathbf{I}^{c})^{+} \in \mathbb{R}^{|\mathcal{V}|\times|\mathcal{E}|}$ distributes the outgoing quantites from the vertices to the edges while solely encoding connectivity and neglecting magnitude.

A.5 Generating Growing Network with Redirection Graph

The GNR graph is built with networkx (Hagberg et al., 2008) by sequentially adding nodes with a link to one previously added node. The previous target node is chosen uniformly at random. With probability p the edge connection is instead "redirected" to the successor node of the target. A probability p closer to 1 leads to broader networks, rather having many edges leading in one central node, while p closer to 0 leads to deeper networks with longer chains leading into a central node. We use an redirection probability of $p = 0$ to attain a deeper network that resembles a river network more closely.

A.6 Causality

In total we moved from a space-continuous description of the state on the edges and vertices during the simulation to a discrete space on the vertices for the measurements. In the continuous advection description, we had a clear cause-effect relation due to the fact that we could look back along an edge or back to previous edges with the edge transition matrix. This continuous description of the causal structure is now subsumed to aggregated, discrete values at nodes and edge connections without an attached domain between them. To be able to incorporate this causal structure into the Graph Neural Controlled Differential Equations (GNCDEs) we have to consider a long enough context window to be able to receive information from the previous vertices at earlier times. The task then resembles learning a delay differential equation.

A.7 Continuous decoder architectures

For forecasting future time steps of the target feature we propose two alternative decoder architectures based on continuous-time extrapolation using NODEs. Both decoder variants replace the final convolutional decoder (see Figure 9), but differ in how the continuous extrapolation is learned: either directly in latent space as a continuation of $\boldsymbol{Z}(t)$ or through a learned extrapolation of the control path $\boldsymbol{X}(t)$ in real space. The decoder variants allow generating predictions within an NCDE framework, where the control path is unknown over the forecasting horizon.

A.7.1 NODE$_g$ continuous decoder.

The first decoder we propose uses $\boldsymbol{Z}(T)$ as the initial condition to an additional NODE whose solution is evaluated at future times $T < t_i \leq T + \tau$ to obtain the final predictions $\{\hat{\mathbf{Y}}_{t_i}\}_{i=1}^{M}$ for the next M time steps up to time $T + \tau$ (see Section A.7.2). This yields the continuous-time evolution

$$\boldsymbol{P}(t) = \boldsymbol{Z}(T) + \int_{T}^{T+t} \boldsymbol{g}_{\boldsymbol{\gamma}}\Big(\boldsymbol{P}(t')\Big)\mathbf{1}\, dt', \tag{18}$$

where $\mathbf{1} \in |\mathcal{V}| \times d_h$ is the matrix of ones and the vector field $\boldsymbol{g}_{\boldsymbol{\gamma}}$ shares its parameters with the encoding $\boldsymbol{g}_{\boldsymbol{\gamma}}$ in Equation (3). Through $\boldsymbol{g}_{\boldsymbol{\gamma}}$, the continued trajectory $\boldsymbol{P}(t)$ contains graph information, depending on the informedness of the inner vector field $\boldsymbol{g}_{\boldsymbol{\gamma}}$. Predictions are obtained by evaluating $\boldsymbol{P}(t_i)$ in latent space at times $T < t_i \leq T + \tau$ and projecting to the data space via a learnable affine layer $l_\delta : \mathbb{R}^{|\mathcal{V}| \times d_z} \to \mathbb{R}^{|\mathcal{V}| \times d_x}$, $\boldsymbol{P}(t_i) \mapsto l_\delta(\boldsymbol{P}(t_i)) = \hat{\mathbf{Y}}_{t_i}$. The choice of $\mathbf{1}$ in Equation (18) reflects the absence of an external control signal beyond time point T. While this is the simplest option, alternative formulations could instead incorporate a learnable control signal. An alternative approach, including such a learnable control is introduced in the following.

A.7.2 NODE$_{ctrl}$ continuous decoder.

For the second decoder type, instead of evolving from $\boldsymbol{Z}(T)$ by a separate NODE and thereby temporally extending the latent space, the observed control $\boldsymbol{X}(t)$ is extended beyond time T by an NODE which learns the vector field $\boldsymbol{h}_{\boldsymbol{\lambda}}$ from data up till T. The state $\boldsymbol{C}(t)$ can be described by

$$\boldsymbol{C}(t) = \boldsymbol{X}(0) + \int_{0}^{t} \boldsymbol{h}_{\boldsymbol{\lambda}}(t', \boldsymbol{C}(t'))\, dt'. \tag{19}$$

To drive the total system, one uses the piecewise control

$$\bar{\boldsymbol{X}}(t) = \begin{cases} \boldsymbol{X}(t), & 0 \leq t \leq T, \\ \boldsymbol{C}(t), & T < t \leq T + \tau. \end{cases} \tag{20}$$

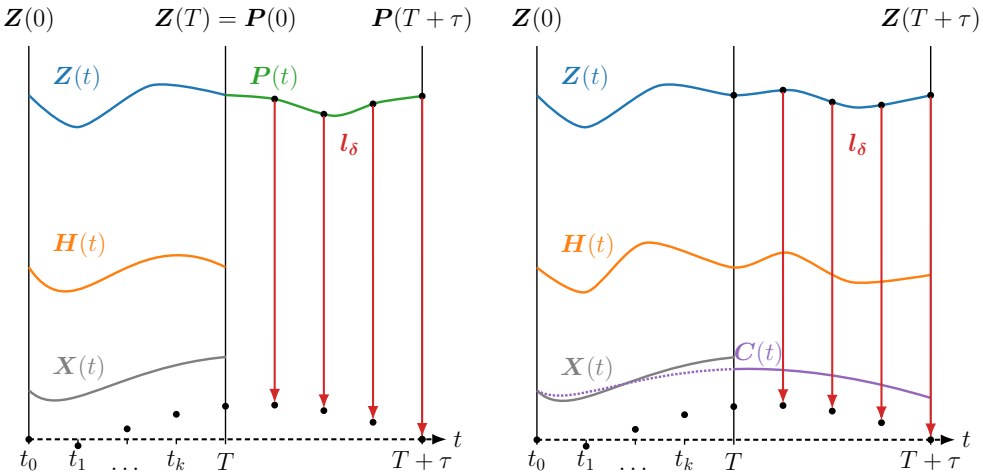
Using $\bar{\boldsymbol{X}}(t)$ in place of the original control yields the jointly coupled system

$$\frac{d}{dt}\begin{bmatrix} \boldsymbol{Z}(t) \\ \boldsymbol{H}(t) \\ \boldsymbol{C}(t) \end{bmatrix} = \begin{bmatrix} \boldsymbol{g}_{\boldsymbol{\gamma}}\Big(\boldsymbol{Z}(t)\Big)\boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\bar{\boldsymbol{X}}(t)}{dt} \\ \boldsymbol{f}_{\boldsymbol{\theta}}\Big(\boldsymbol{H}(t)\Big)\frac{d\bar{\boldsymbol{X}}(t)}{dt} \\ \boldsymbol{h}_{\boldsymbol{\lambda}}\Big(t, \boldsymbol{C}(t)\Big) \end{bmatrix}. \tag{21}$$

Accordingly, the hidden states $\boldsymbol{H}(t)$ and $\boldsymbol{Z}(t)$ are driven by the observed path on $[0, T]$ and by the learned continuation on $(T, T+\tau]$. Forecasts are again obtained by evaluating the evolved latent states $\boldsymbol{Z}(t_i)$ at times $T < t_i \leq T + \tau$ and mapping them to the target space via a learnable linear layer $\boldsymbol{Z}(t_i) \mapsto l_\delta(\boldsymbol{Z}(t_i)) = \hat{\mathbf{Y}}_{t_i}$, analogous to the NODE$_g$ decoder (see Section A.7.1). Since, in this decoder setting, the NODE of $\boldsymbol{C}(t)$ is trained in parallel to the NCDE, we employ two loss terms: the standard NCDE loss and an additional loss $\mathcal{L}(\{\mathbf{C}_{t_j}\}, \{\mathbf{X}_{t_j}\})$ on the control, which is evaluated over the entire time window $0 \leq t_j \leq T + \tau$. During training, this term is scaled by a factor of 1/epoch, such that the control loss receives a substantially higher relative weight at the beginning of training, which gradually decreases towards the end.

A.8 Additional Experimental Results

In this section we provide further material regarding the experimental results for the advection data, river discharge task and the PeMS08 traffic flow dataset, and results regarding the different Decoder settings.



(a) NODE decoder

(b) $\text{NODE}_{\text{ctrl}}$ decoder

Figure 9: Graphical overview of the NCDE encoder-decoder structure in combination with two continuous decoder variants on the right halves in (a) and (b). **(a)**: NODE_g-decoder evolves a hidden state $\boldsymbol{P}$ for $t > T$ via an NODE, based on the last hidden state $\boldsymbol{Z}(T)$ over time via an NODE. Predictions can be read out at any given time via an affine layer (red). **(b)**: NODE_{ctrl}-decoder allows for continuous evolution of $\boldsymbol{Z}$ and $\boldsymbol{H}$ into the prediction time window by learning an extrapolation $\boldsymbol{C}$ of the control signal $\boldsymbol{X}$. The readout of predictions is identical to NODE_g.

A.9 Advection simulation data

For the advection simulation data, we additionally provide the table results of the variants of the main part in Table 4. Moreover we compared further outer-inner graph informedness variations whose results can be found in Table 5.

Table 4: MAE for different outer-inner informedness mechanisms for graphs with increasing graph nodes, and increasing node resolution along the edges

	Outer	**Inner**	**Nodes**	**Spatial resolution**		
				1	2	4
STG-NCDE	Identity	AGC	4	0.75 ±0.0513	0.76 ±0.0526	0.83 ±0.0926
STG-NCDE	Identity	AGC	8	0.96 ±0.0476	0.99 ±0.0678	1.22 ±0.1951
STG-NCDE	Identity	AGC	16	1.65 ±0.1424	2.10 ±0.2567	2.98 ±0.4047
STG-NCDE	Identity	AGC	32	2.90 ±0.2319	4.58 ±0.7343	5.07 ±0.4969
STG-NCDE	Identity	AGC	64	5.64 ±0.1174	–	–
STG-NCDE	Identity	AGC	128	5.42 ±0.0614	–	–
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	4	0.72 ±0.0297	0.73 ±0.0524	0.79 ±0.0422
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	8	0.91 ±0.0292	1.03 ±0.0680	1.07 ±0.0624
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	16	1.18 ±0.0806	1.39 ±0.0563	2.11 ±0.1038
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	32	1.07 ±0.0981	1.25 ±0.0579	2.93 ±0.3218
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	64	1.01 ±0.0563	–	–
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	128	0.89 ±0.0391	–	–
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	4	0.92 ±0.0716	1.07 ±0.1482	2.01 ±0.1266
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	8	1.11 ±0.0716	1.40 ±0.0868	2.50 ±0.1993
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	16	1.41 ±0.1144	1.73 ±0.2232	3.36 ±0.4732
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	32	1.39 ±0.2397	1.55 ±0.1440	3.10 ±0.5847
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	64	1.44 ±0.2252	–	–
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	128	1.60 ±0.2624	–	–

A.9.1 Water discharges

For the water discharge task, we additionally compared different mechanisms at the outer and inner positions shown in Table 6 and different adjacency matrix powers in Section A.9.1 and Table 7.

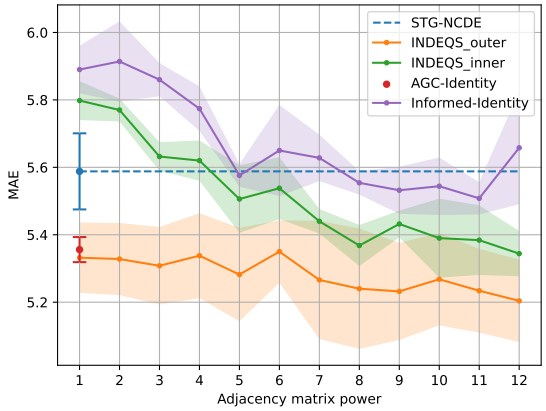


Figure 10: Average performance of INDEQS and additional informedness variations, with increasing adjacency matrix powers vs. the uninformed STG-NCDE for the task of water discharges over 5 runs.

A.9.2 PeMS08 traffic flow

For the traffic flow task, we show results and properties of 2 additional outer-inner graph information strategies in Table 8 and also results for higher adjacency matrix powers in Table 9.

A.9.3 Result comparison among decoder types

We compare the discrete convolutional decoder with the continuous decoder architectures introduced in Section A.7, namely NODE_g and NODE_{ctrl}, on the advection simulation, river discharge and traffic forecasting tasks. The corresponding results are reported in Tables 10-13. In both real-world settings, the continuous decoders outperform the discrete convolutional decoder in terms of both validation and test MAE, indicating the advantage of continuous-time decoding for these tasks. While NODE_{ctrl} achieves the best performance on the river discharge task, NODE_g appears, on average, to be the strongest option for traffic forecasting.
A practical advantage of NODE_g over NODE_{ctrl} is that it improves MAE without introducing additional hyperparameters, while also requiring fewest trainable parameters. More generally, the superior performance of the continuous decoder architectures comes at the cost of increased computational time, since in both cases the hidden-state trajectories $\boldsymbol{Z}$ must also be solved over the prediction window. This effect is most pronounced for NODE_{ctrl}, as the NODE governing the learned control signal $\boldsymbol{C}$ must be solved in addition to the continuation of the hidden-state trajectories $\boldsymbol{Z}$ and $\boldsymbol{H}$.
For the advection simulation task however, the continuous decoders perform significantly worse than the convolutional prediction head (see Table 10 and Table 11).

A.9.4 Comparison of solvers and step-sizes for all decoder architectures

We compare the three decoder architectures on the water discharge task across combinations of numerical solvers and solver step sizes. The results are shown in Figure 11, which reports validation MAE and training time as a function of the solver step size. Across all decoders, we observe a solver-specific optimal step size that yields the best trade-off between predictive performance and computational cost. Decreasing the step size beyond this point consistently increases training time, while providing little or no additional improvement in MAE. For the smallest step sizes, *Euler* and *RK4* achieve comparable MAE, although *RK4* remains substantially more expensive computationally. To ensure consistency across experiments, we

use *RK4* with step size 1 in all main results. However, if the best performance needs to be achieved, the solver configuration may depend on the decoder architecture. For example, the NODE_{ctrl} decoder (Fig. 11, right) appears to perform best with the computationally cheaper *Euler* solver at step size 0.5, while the convolutional decoder (Fig. 11, left) may benefit from *Euler* with step size 0.25 and NODE_g may be used with either *Euler* 0.25 or *RK4* 1.0.

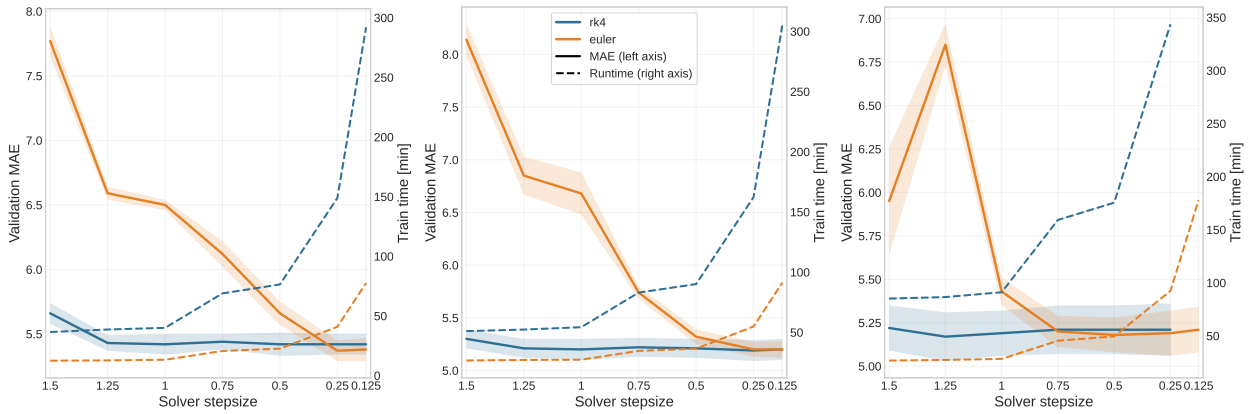


Figure 11: MAE and runtime for different solver and step-size combinations for the discrete convolutional decoder (left), the continuous NODE_g decoder (center) and the continuous NODE_{ctrl} decoder (right). All experiments were performed on the **water discharge** prediction task and run for 200 epochs. Standard deviation over 5 runs is displayed as shaded area.

A.10 Software

For data preparation *numpy* (Harris et al., 2020), *scipy* (Virtanen et al., 2020) and *pandas* (Wes McKinney, 2010; pandas development team, 2020) was used. Plots were created with *matplotlib* (Hunter, 2007). The model code is based on Choi et al. (2022)'s code and relies on *pytorch* (Paszke et al., 2017; 2019), *torchdiffeq* Chen (2018) and *controldiffeq* (Kidger et al., 2020). To monitor training runs we used *tensorboard* (Abadi et al., 2015). The cluster for the experiments ran images of *Ubuntu 20.04* with *NVIDIA CUDA 11.7.1* and *CUDNN 9*.

A.11 Hardware

All experiments were conducted on a cluster node with an AMD EPYC 73F3 3.5 GHz with 16 cores and 64 GB RAM, and a NVIDIA A100 with 40 GB VRAM.

Table 5: MAE for different outer-inner informedness mechanisms for graphs with increasing graph nodes, and increasing node resolution along the edges

Label	Outer	Inner	Nodes	Spatial resolution		
				1	2	4
	AGC	AGC	4	0.79 ±0.0321	0.72 ±0.0358	0.85 ±0.0850
	AGC	AGC	8	0.98 ±0.0614	1.05 ±0.1154	2.51 ±0.9738
	AGC	AGC	16	1.66 ±0.3254	3.70 ±1.1690	5.08 ±0.6714
	AGC	AGC	32	4.49 ±1.1091	5.33 ±0.0875	5.41 ±0.0370
	AGC	AGC	64	5.78 ±0.0332	–	–
	AGC	AGC	128	5.52 ±0.0324	–	–
	AGC	Identity	4	1.41 ±0.3518	1.19 ±0.1933	1.50 ±0.3887
	AGC	Identity	8	2.23 ±0.7419	1.79 ±0.6673	1.80 ±0.2517
	AGC	Identity	16	3.08 ±0.5545	2.99 ±0.8873	4.27 ±1.1252
	AGC	Identity	32	3.33 ±0.4909	4.41 ±0.9618	5.34 ±0.0546
	AGC	Identity	64	5.24 ±0.5101	–	–
	AGC	Identity	128	5.46 ±0.0434	–	–
	AGC	informed	4	0.80 ±0.0760	0.94 ±0.0750	0.91 ±0.0909
	AGC	Informed	8	1.01 ±0.0251	1.19 ±0.0274	1.29 ±0.3112
	AGC	Informed	16	1.38 ±0.0502	1.67 ±0.0789	2.90 ±0.0532
	AGC	Informed	32	1.56 ±0.0428	1.76 ±0.0430	2.85 ±0.1536
	AGC	Informed	64	2.22 ±0.0421	–	–
	AGC	Informed	128	2.44 ±0.0316	–	–
STG-NCDE	Identity	AGC	4	0.75 ±0.0513	0.76 ±0.0526	0.83 ±0.0926
STG-NCDE	Identity	AGC	8	0.96 ±0.0476	0.99 ±0.0678	1.22 ±0.1951
STG-NCDE	Identity	AGC	16	1.65 ±0.1424	2.10 ±0.2567	2.98 ±0.4047
STG-NCDE	Identity	AGC	32	2.90 ±0.2319	4.58 ±0.7343	5.07 ±0.4969
STG-NCDE	Identity	AGC	64	5.64 ±0.1174	–	–
STG-NCDE	Identity	AGC	128	5.42 ±0.0614	–	–
	Identity	Identity	4	4.05 ±0.0451	4.03 ±0.0421	4.03 ±0.0390
	Identity	Identity	8	4.92 ±0.0167	4.92 ±0.0274	4.93 ±0.0351
	Identity	Identity	16	6.21 ±0.0365	6.21 ±0.0472	6.25 ±0.0217
	Identity	Identity	32	5.89 ±0.0179	5.92 ±0.0327	5.98 ±0.0474
	Identity	Identity	64	6.30 ±0.0513	–	–
	Identity	Identity	128	6.25 ±0.0292	–	–
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	4	0.92 ±0.0716	1.07 ±0.1482	2.01 ±0.1266
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	8	1.11 ±0.0716	1.40 ±0.0868	2.50 ±0.1993
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	16	1.41 ±0.1144	1.73 ±0.2232	3.36 ±0.4732
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	32	1.39 ±0.2397	1.55 ±0.1440	3.10 ±0.5847
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	64	1.44 ±0.2252	–	–
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	128	1.60 ±0.2624	–	–
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	4	0.72 ±0.0297	0.73 ±0.0524	0.79 ±0.0422
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	8	0.91 ±0.0292	1.03 ±0.0680	1.07 ±0.0624
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	16	1.18 ±0.0806	1.39 ±0.0563	2.11 ±0.1038
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	32	1.07 ±0.0981	1.25 ±0.0579	2.93 ±0.3218
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	64	1.01 ±0.0563	–	–
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	128	0.89 ±0.0391	–	–
	Informed	Identity	4	0.98 ±0.0822	1.10 ±0.1529	2.42 ±0.7735
	Informed	Identity	8	1.17 ±0.1452	1.43 ±0.3069	2.73 ±0.7580
	Informed	Identity	16	1.40 ±0.1421	1.96 ±0.2817	3.91 ±0.8507
	Informed	Identity	32	1.44 ±0.3059	1.65 ±0.1366	3.27 ±0.6967
	Informed	Identity	64	1.49 ±0.1657	–	–
	Informed	Identity	128	1.57 ±0.2370	–	–
	Informed	Informed	4	0.91 ±0.1468	0.98 ±0.1601	1.80 ±0.5672
	Informed	Informed	8	1.02 ±0.0843	1.50 ±0.2582	2.17 ±0.2936
	Informed	Informed	16	1.29 ±0.1230	1.76 ±0.1038	2.80 ±0.2686
	Informed	Informed	32	1.50 ±0.1785	1.94 ±0.2183	2.35 ±0.1228
	Informed	Informed	64	1.59 ±0.2592	–	–
	Informed	Informed	128	1.63 ±0.2187	–	–

Table 6: Overview of MAE, number of parameters, training time and epoch of last improvement, with standard deviations, for different outer-inner configurations for the **water discharge** prediction over 5 runs with different random seeds.

	Outer	**Inner**	**MAE**	**# Params.**	**MAE (val.)**	**Train time**	**Last improvement**
	AGC	Identity	5.36 ±0.04	415,879	5.31 ±0.05	40.11 min ±0.25	191.20 ±3.27
	AGC	LGC	5.43 ±0.10	539,399	5.36 ±0.09	50.34 min ±0.41	161.20 ±39.95
	AGC	Informed	**5.33** ±0.04	415,879	5.31 ±0.05	39.97 min ±0.14	186.00 ±7.11
STG-NCDE	Identity	AGC	5.59 ±0.13	415,879	5.64 ±0.18	37.85 min ±0.13	188.40 ±10.92
	Identity	Identity	5.94 ±0.01	291,909	6.13 ±0.01	28.06 min ±0.14	175.60 ±8.08
	Identity	LGC	5.86 ±0.03	415,429	5.94 ±0.02	38.34 min ±0.13	128.00 ±16.23
$\text{INDEQS}_{\text{inner}}$	Identity	Informed	5.80 ±0.06	291,909	5.92 ±0.03	28.02 min ±0.12	177.40 ±26.52
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	<u>5.33</u> ±0.12	415,879	5.43 ±0.09	40.14 min ±0.09	167.60 ±29.42
	Informed	Identity	5.89 ±0.08	291,909	5.99 ±0.06	30.28 min ±0.06	181.00 ±14.00
	Informed	LGC	5.95 ±0.02	415,429	6.01 ±0.03	40.40 min ±0.23	88.00 ±10.02

Table 7: MAE with standard deviation over 5 runs for different outer-inner graph configurations for increasing powers of the adjacency matrix for the **water discharge** prediction.

	Adjacency matrix power											
	1	2	3	4	5	6	7	8	9	10	11	12
Informed - Identity	5.89 ±0.07	5.91 ±0.12	5.86 ±0.05	5.77 ±0.07	5.58 ±0.03	5.65 ±0.14	5.63 ±0.07	5.55 ±0.03	5.53 ±0.07	5.54 ±0.09	5.51 ±0.05	5.66 ±0.17
$\text{INDEQS}_{\text{outer}}$	5.33 ±0.10	5.33 ±0.11	5.31 ±0.12	5.34 ±0.13	5.28 ±0.14	5.35 ±0.09	5.27 ±0.18	5.24 ±0.18	5.23 ±0.14	5.27 ±0.14	5.23 ±0.12	**5.20** ±0.12
$\text{INDEQS}_{\text{inner}}$	5.80 ±0.06	5.77 ±0.03	5.63 ±0.04	5.62 ±0.06	5.51 ±0.10	5.54 ±0.09	5.44 ±0.04	5.37 ±0.06	5.43±0.04	5.39 ±0.12	5.38 ±0.10	5.34 ±0.07
AGC - Informed	5.33 ±0.03	5.33 ±0.02	5.33 ±0.06	5.33 ±0.05	5.32 ±0.05	5.29 ±0.02	5.26 ±0.02	5.29 ±0.04	5.33 ±0.03	5.28 ±0.07	5.29 ±0.02	5.28 ±0.08

Table 8: Overview of MAE, number of parameters, training time and the epoch when validation loss last improved, with standard deviations, for different outer-inner configurations for the **PeMS08 traffic** prediction over 5 runs with different random seeds.

	Outer	**Inner**	**MAE (test)**	**#Params.**	**MAE (val.)**	**Train time**	**Last improvement**
	AGC	Identity	17.85 ±0.40	45,152	18.51 ±0.48	135.49 min ±0.88	196.60 ±1.82
	AGC	Informed	17.24 ±0.12	45,152	17.80 ±0.17	135.24 min ±1.19	175.80 ±30.78
STG-NCDE	Identity	AGC	16.55 ±0.20	45,152	17.00 ±0.22	129.31 min ±1.04	183.00 ±3.94
$\text{INDEQS}_{\text{outer}}$	Informed	AGC	**16.50** ±0.19	45,152	16.88 ±0.28	143.18 min ±1.45	169.00 ±11.20

Table 9: MAE with standard deviation over 5 runs for different outer-inner graph configurations for increasing powers of the adjacency matrix for the **PeMS08 traffic** prediction.

	Adjacency matrix power				
	1	2	3	4	5
AGC - Informed	17.24 ±0.11	17.22 ±0.30	17.13 ±0.18	17.27 ±0.21	17.23 ±0.23
AGC - Identity	17.85 ±0.36	-	-	-	-
$\text{INDEQS}_{\text{outer}}$	16.50 ±0.17	**16.39** ±0.18	16.53 ±0.13	16.53 ±0.19	16.53 ±0.12
STG-NCDE	16.55 ±0.18	-	-	-	-

Table 10: Mean test MAE with standard deviation over 5 runs, the best test MAE of these, number of parameters, mean validation MAE with standard deviation and train time for different decoder architectures for $\text{INDEQS}_{\text{outer}}$ for the **advection simulation** prediction on a graph with 64 nodes with training for **200 epochs**.

Decoder type	**MAE**	**best MAE**	**#Params.**	**MAE (Val.)**	**Train time**
convolutional(discrete)	**1.01** ±0.06	0.92	72,396	**1.00** ±0.05	**20.31** min ±0.11
NODE_g (continuous)	2.81 ±0.51	2.28	72,033	2.76 ±0.53	30.91 min ±0.18
NODE_{ctrl} (continuous)	2.95 ±0.20	2.62	74,274	2.92 ±0.19	51.63 min ±1.33

Table 11: Mean test MAE with standard deviation over 5 runs, the best test MAE of these, number of parameters, mean validation MAE with standard deviation and train time for different decoder architectures for $\text{INDEQS}_{\text{outer}}$ for the **advection simulation** prediction on a graph with 64 nodes with training for **400 epochs**.

Decoder type	**MAE**	**best MAE**	**#Params.**	**MAE (Val.)**	**Train time**
convolutional(discrete)	**0.92** ±0.05	0.86	72,396	**0.91** ±0.05	**41.22** min ±0.13
NODE_g (continuous)	2.14 ±0.47	1.48	72,033	2.10 ±0.47	62.86 min ±0.41
NODE_{ctrl} (continuous)	2.15 ±0.24	1.98	74,274	2.11 ±0.25	104.51 min ±1.30

Table 12: Mean test MAE with standard deviation over 5 runs, the best test MAE of these, number of parameters, mean validation MAE with standard deviation and train time for different decoder architectures for $\text{INDEQS}_{\text{outer}}$ for the **water discharges** prediction.

Decoder type	**MAE**	**best MAE**	**#Params.**	**MAE (Val.)**	**Train time**
convolutional(discrete)	5.30 ±0.15	5.15	415,879	5.43 ±0.09	**41.35** min ±2.05
NODE_g (continuous)	5.07 ±0.08	4.96	415,619	**5.20** ±0.10	54.78 min ±1.31
NODE_{ctrl} (continuous)	**5.01** ±0.16	**4.84**	416,500	<u>5.20</u> ±0.14	92.00 min ±0.84

Table 13: Mean test MAE with standard deviation over 5 runs, the best test MAE of these, number of parameters, mean validation MAE with standard deviation and train time for different decoder architectures for $\text{INDEQS}_{\text{outer}}$ for the **PeMS08 traffic** prediction.

Decoder type	**MAE**	**best MAE**	**#Params.**	**MAE (Val.)**	**Train time**
convolutional(discrete)	16.50 ±0.19	16.25	45,152	16.88 ±0.28	**143.72** min ±0.47
NODE_g (continuous)	**16.27** ±0.09	**16.12**	44,789	**16.63** ±0.09	220.87 min ±2.85
NODE_{ctrl} (continuous)	16.37 ±0.12	16.20	47,030	16.75 ±0.21	365.49 min ±2.24

A.12 Notational conventions

Nomenclature

Advection Simulation

$\delta(e)$	Edge length
$\mathbf{A}_{\mathcal{E}}$	(Directed) edge transition matrix
$\mathbf{v}$	Velocity vector field
$\mathbf{y}$	Vector field of advected quantity
Ω_e	Continuous edge domain
$a_{ij} \in \mathbf{A}_{\mathcal{E}}$	Matrix elements
p_{ij}	Edge transition probability
V_e	Function space on edge

Neural Differential Equations

$\boldsymbol{f_\theta}, \boldsymbol{g_\gamma}$	Vector field matrices
$\boldsymbol{H}(t), \boldsymbol{Z}(t)$	Hidden state matrices
$\boldsymbol{X}(t)$	Control matrix
$\mathcal{T} = [0, T]$	Training time interval
τ	Final prediction time point
d_Z, d_H	Hidden state matrix dimensions
d_z, d_h	Hidden path dimensions (per node)
M	Number of prediction timesteps
$t \in \mathcal{T}$	Virtual time
T	Final training time point

Experimental input

d_x	Dimension of data input (per node)
s	Arbitrary parametrization
t_i	Observation time points
$x(s)$	Interpolated data input
$x_i($	Data input (discrete)

Graph Structure

$\mathcal{E}$	Set of edges
$\mathcal{G}$	Directed graph
$\mathcal{V}$	Set of vertices/nodes
$e \in \mathcal{E}$	Edge
$v \in \mathcal{V}$	Vertex/node

INDEQS specific

$\boldsymbol{A}_{\mathcal{V}}^{\text{inner}}$	Inner vertex transition matrix
$\boldsymbol{A}_{\mathcal{V}}^{\text{outer}}$	Outer vertex transition matrix
$\boldsymbol{E}$	Node embedding matrix
$\boldsymbol{I}$	Identity matrix
$\mathbf{A}_{\mathcal{V}}$	Vertex adjacency matrix
$\mathbf{I}$	Vertex incidence matrix
B	Bias vector
C	Node embedding dimension
W	Weight transformation matrix

Neural Networks (general)

$\hat{\mathbf{Y}}$	Prediction
$\mathbf{Y}$	Ground truth
$\mathcal{L}$	Loss function
ϕ	Softmax activation
σ	Rectified linear unit (ReLU) activation
θ, γ	Neural network parameters
d_y	Hidden state dimension (per node)
$l_\theta(y)$	Decoder: (convolutional) affine layer
$m_\theta(x)$	Encoder: (linear) affine layer
y	Hidden state variable

A.13 Comparative overview of Graph Neural Differential Equation methods

In Table 14 and Table 15 we compare INDEQS to Graph Neural Differential Equations methods that are most similar.

Table 14: Comparative overview of Graph Neural Differential Equations methods.

	INDEQS (this work)	STG-NCDE (Choi et al., 2022)	GDE (Poli et al., 2021)	GN-CDE (Qin et al., 2026)	NDCN Zang & Wang (2020)	STGODE (Fang et al., 2021)
Code available	✔	✔	✔	✗	✔	✔
Control	Continuous-time node feature control	Continuous-time node feature control	Discrete node feature control via GRU	Continuous-time (graph structure + feature) control	✗	✗
NDE/DE structure	2 stacked 1st order NCDEs	2 stacked 1st order NCDEs	1st/2nd order NODE	1st order NCDE	1st order NODE	2 chained sets of 3 parallel blocks of 1st order NODEs
Graph dynamics	Static	Static	Discretely dynamic	Continuously dynamic	Static	Static
Graph informed	✔	✗	✔	✔	✔	✔
Spatial processing	Adjacency matrix + adaptive graph convolution	Adaptive graph convolution	Graph convolution (laplacian) in vector field	Adjacency matrix as Control	Linear diffusion operator in vector field	2 adjacency matrices in vector field
Edge features processing	✗	✗	✗	✗	✗	✗
Spatial domain	Discrete	Discrete	Discrete	Discrete	Discrete	Discrete
Temporal architecture	NCDE, convolutional layer	NCDE, convolutional layer	NODE with GRU jumps	NCDE	NODE	TCN (Bai et al., 2018)
Irregular data	✔	✔	✔	✔	✔	✗
Internal temporal data processing	Continuous encoding on context window, Discrete decoding on horizon	Continuous along NCDE time dimension	Continuous with virtual jumps along NODE time dimension	Continuous along NCDE time dimension	Continuous along NODE time dimension	all-at-once (NODE orthogonal to time dimension)

Continued on next page

Table 14: Comparative overview of Graph Neural Differential Equations methods. (Continued)

	INDEQS (this work)	STG-NCDE (Choi et al., 2022)	GDE (Poli et al., 2021)	GN-CDE (Qin et al., 2026)	NDCN Zang & Wang (2020)	STGODE (Fang et al., 2021)
Application domains	Hydrology, traffic flow, graph edge advection	Traffic flow	Citation networks, mechanical multi-particle system, traffic speed	Heat diffusion, mutualistic interaction, gene regulation	Heat diffusion, mutualistic interaction, gene regulation	Traffic speed/flow
Tasks	Structured sequence forecasting	Structured sequence forecasting	Transductive node classification, Multi–agent trajectory extrapolation, Forecasting	Continuous-time network dynamics prediction, Structured sequence prediction, Node semi-supervised classification	Continuous-time network dynamics prediction, Structured sequence prediction,NDE Node semi-supervised classification	Structured sequence forecasting

Table 15: Comparative overview of Graph Neural Differential Equations methods.

	INDEQS (this work)	CG-ODE Huang et al. (2021)	CF-GODE Jiang et al. (2023a)	HOPE Luo et al. (2023)	GRAM-ODE Liu et al. (2023)	AG-NCDE Yao & Zhou (2025)
Code available	✔	✔	✗	✗	✔	✗
Control	Continuous-time node feature control	✗	✗	✗	✗	Continuous-time node feature control
NDE/DE structure	2 stacked 1st order NCDEs	2 coupled ODEs (nodes, edges)	ODE parametr. by GNN	2 coupled 2nd order ODEs (nodes, edges)	3 coupled blocks of GNN based ODEs (global, local, edge)	2 stacked 1st-order NCDEs
Graph dynamics	Static	Dynamic	Static	Dynamic	Dynamic	Dynamic
Graph informed	✔	✔	✔	✔	✔	✗

Continued on next page

Table 15: Comparative overview of Graph Neural Differential Equations methods. (Continued)

	INDEQS (this work)	CG-ODE Huang et al. (2021)	CF-GODE Jiang et al. (2023a)	HOPE Luo et al. (2023)	GRAM-ODE Liu et al. (2023)	AG-NCDE Yao & Zhou (2025)
Spatial processing	Adjacency matrix + adaptive graph convolution	GNN in initial encoder	GNN in vector field	Spatial + spectral convolution	Adjacency (connection map + DTW graph) + dynamic semantic edges	NCDE + inferred, dynamic adjacency Matrix + graph convolution
Edge features processing	✗	✔	✔	✔	✔	✗
Spatial domain	Discrete	Discrete	Discrete	Discrete	Discrete	Discrete
Temporal architecture	NCDE, convolutional layer	GNN + temp. self attention	NODE	Spatial + spectral convolution + temp. self attention	TCN + multi ODE-GNN + multi-head attention	NCDE + external attention on two time scales
Irregular data	✔	✔	✗	✗	✗	✔
Internal temporal data processing	Continuous encoding on context window, discrete decoding on horizon	Discrete encoding along context window, continuous decoding along horizon window	Continuous decoding via NODE	Discrete encoding, continuous decoding	Discrete encoding via TCN, continuous processing via ODE-GNNs, discrete decoding on horizon	Continuous encoding on context window, discrete decoding on horizon
Application domains	Hydrology, traffic flow, graph edge advection	Disease spread	Disease control	Disease spread, Opinion migration on social networks, Spring oscillation	Traffic flow	Traffic flow
Tasks	Structured sequence forecasting	Forecasting	Causal inference, counterfactual outcomes	Sequence representation Learning	Forecasting	Forecasting

A.14 River network maps

The river topology of the river discharge task is depicted in Figure 12.

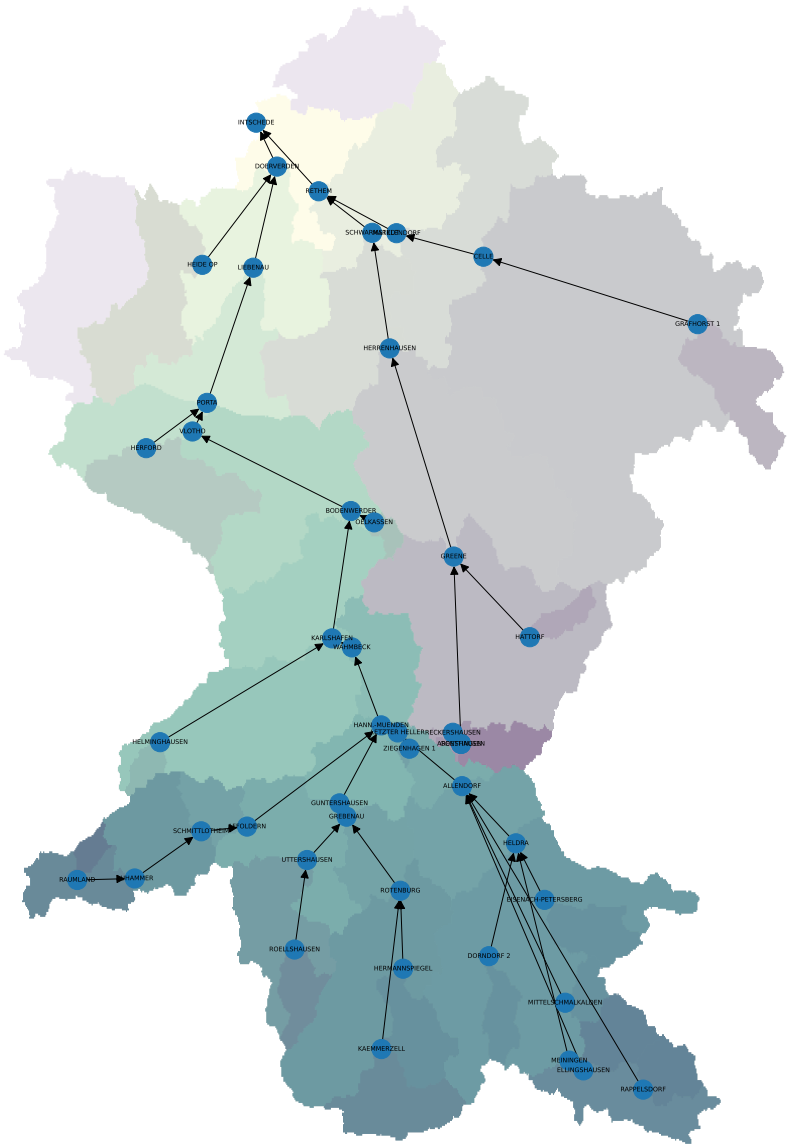


Figure 12: The graph network of the discharge stations of the Weser river and their catchments