A Systematic Literature Review of Spatio-Temporal Graph Neural Network Models for Time Series Forecasting and Classification

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October 2024

Abstract

In recent years, spatio-temporal graph neural networks (GNNs) have attracted considerable interest in the field of time series analysis, due to their ability to capture dependencies among variables and across time points. The objective of the presented systematic literature review is hence to provide a comprehensive overview of the various modeling approaches and application domains of GNNs for time series classification and forecasting. A database search was conducted, and over 150 journal papers were selected for a detailed examination of the current state-of-the-art in the field. This examination is intended to offer to the reader a comprehensive collection of proposed models, links to related source code, available datasets, benchmark models, and fitting results. All this information is hoped to assist researchers in future studies. To the best of our knowledge, this is the first systematic literature review presenting a detailed comparison of the results of current spatio-temporal GNN models in different domains. In addition, in its final part this review discusses current limitations and challenges in the application of spatio-temporal GNNs, such as comparability, reproducibility, explainability, poor information capacity, and scalability.

1 Introduction

In recent years, graph neural networks (GNNs) have emerged as a powerful class of artificial neural network models for processing data that can be represented as graphs. GNNs are in fact particularly well-suited for a wide range of practical and engineering applications where data naturally lend themselves to be represented as graph structures, such as applications to transportation networks, image analysis, and natural language processing. The intuitive concept behind this approach is that nodes in a graph can be put in correspondence to objects or concepts, whereas edges can be assumed to represent their mutual relationships. Data for these quantities can then be processed at once by a GNN model. GNNs can be used for three different classes of problems: at graph level, at edge level, and at node level. In a graph-level problem, the goal is to predict a property of a graph based on its entire structure, rather than on individual nodes or edges. For example, a molecule from a sample can be represented as a graph, and global properties of this molecule can be inferred from data coming from its entire structure in relation to the sample. In an edge-level problem, the goal is to predict the presence or absence of edges between pairs of nodes. As an example, this task can be used in recommendation systems to predict potential connections between users and items on the basis of past interactions. In node-level problems, the goal is to predict the identity or role of each node within a graph, in order to solve either a classification or a regression task. Noticeably, regression tasks can be "autoregressions", that is, they can include time.

This review examines then the specific use of GNNs on time series related tasks, with a particular focus on time series classification and forecasting. The idea behind the use of GNNs for time series problems is that GNNs can be made capable of capturing complex relationships, both inter-variable (connections between different variables within a multivariate series) but also inter-temporal (dependencies between different points in time) at once. This results in a *spatio-temporal* GNN approach, where the spatial dimension is related to the multivariate framework, and the temporal dimension is related to the temporal nature of the data. Namely, spatio-temporal GNNs are a class of GNN models designed to handle data in both spatial and temporal dimensions at once. In this case, in a spatio-temporal graph, data in each node or edge can evolve over time, and the challenge is here to model the related dynamic interactions over time.

Notwithstanding all this potential interest, to the best of our knowledge there is a lack of systematic literature reviews (SLRs) on spatio-temporal GNN models for time series applications. Most of the existing surveys are not SLRs, they are not recent, or only focus on a limited number of application domains. Individually, recent reviews focus for example on algorithmic features [9], [132], [200], [18], GNN characterization [199], specific fields [80], and distributed training [125], [162]. Only a SLR on spatio-temporal GNNs was indeed recently published by Zeghina et al. [223], but due to the restrictive search query, it covers only 52 publications.

The intention of the SLR presented here is to provide a broad and comprehensive overview of the applications of spatio-temporal GNNs for time series classification and forecasting in different areas. This SLR also aims to assess if the current popularity of spatio-temporal GNN models is indeed due to their effectiveness, and to evaluate their efficacy and accuracy in different fields. Additionally, it collects results and benchmarks to assist researchers in their work by synthesizing the available literature on GNN applications. To the best of our knowledge, this is the first review to present comprehensive tables with all the results from the various models and benchmarks proposed in a highly fragmented literature. It is thus hoped that this collected and distilled knowledge can become a valuable resource and reference for researchers.

In this review two sets of questions will be posed. The answers to the first set want to provide a general overview of the publications in the field, while the answers to the second set focus on specific aspects of the proposed GNN models.
The general overview questions (GQs) are:

- GQ1) **Trend**: What is the temporal trend of publications on GNN models? Is there a growing interest in GNNs?
- GQ2) **Fields**: In which fields are GNN models most commonly applied?
- GQ3) **Journals**: In which journals are the papers on GNNs published? Are these journals chosen because of the specific domain of application or not?
- GQ4) **Research groups**: Which are the most active research groups on GNNs?
- GQ5) **Tools**: What tools (programming languages, libraries, frameworks) are used to implement the GNN models?
- GQ6) **Fundings**: Did the authors of the papers receive public or private funding for their research?

The specific questions (SQs) are:

- SQ1) **Applications**: Which are the most studied applications of spatio-temporal GNNs? Are there differences in approaches and results across different application areas?
- SQ2) **Graph construction**: Is the graph structure predetermined? If not, how do researchers define it?
- SQ3) **Taxonomy**: Among the various taxonomy classes, which are the most common? Are there some recurring mechanisms?
- SQ4) **Benchmark models**: Which are the most common benchmark models? Are they classical ML models or also GNN models?
- SQ5) **Benchmark datasets**: Which are the most common benchmark datasets?

SQ6) **Modeling paradigms**: What is the most common paradigm? Is it modeling complex interacting systems, or modeling a system with multiple interacting quantities? Specifically, do graphs typically condense the relationships among multiple entities, or do they describe different aspects of the same entity? In other words, is the graph structure homogeneous or heterogeneous?

SQ7) **Metrics**: Which are the most common metrics used to assess the accuracy of a given model?

The answers to both the general and the specific questions will be integrated into the following discussion in order to provide a comprehensive overview of the present state-of-the-art of spatio-temporal GNN models. A general overview of such GNN models will be assembled by highlighting similarities and differences between the approaches across different fields. However, in case, for a more detailed analysis of a specific discipline or other aspects of GNN models, the reader is invited to consult the specialized reviews mentioned before ([9], [132], [200], [18], [199], [80], [125], [162]).

The paper is organized as follows. After this Introduction, Sec. 2 illustrates the methodology used to collect the papers. Sec. 3 provides a general overview of the selected papers. Sec. 4 introduces some fundamental definitions and notions at the basis of spatio-temporal GNN models, and discusses their taxonomy and the determination of the graph structure. Sec. 5 is the core of this review. It explores the diverse domains of application of the spatio-temporal GNN models proposed in the selected papers for the identified domains. A discussion of the findings and the answers to the research questions mentioned above are provided in Sec. 6. Finally, limits, challenges and future research directions are presented in Sec. 7. Sec. 8 concludes the review. Appendix A provides a list of all journal papers included in this SLR, together with the year of publication, group they belong to, case study, and nature of the task (e.g., classification or forecasting).

2 Methodology for the systematic literature review

To conduct this SLR, four primary databases were consulted: Scopus, IEEE Xplore, Web of Science, and ACM. These databases were chosen for their comprehensive coverage of academic and scientific literature, ensuring a broad and inclusive search across multiple disciplines.

Prior to commencing the literature search, some exclusion criteria were defined. First, papers from the current year 2024 were excluded because it has not yet ended, hence the review only covers up to year 2023. Second, only journal articles were considered, in order to guarantee the inclusion of "established" sources, whereas both conference papers and book chapters were excluded. The exclusion of conference papers is also made in order to keep the number of papers manageable. However, it is important to notice that relevant conference papers which provide useful benchmarks are anyway referenced throughout the text. Third, only articles published in English were included because of facility of fruition and comparison. Review articles are also not included, although they may be mentioned in the test.

An advanced search query submitted to the databases was designed to capture the breadth of the topic while maintaining specificity. The query used is `(("graph neural network" OR gnn) AND "time series") AND (classification OR forecasting)`. The first two elements of query aim to restrict the pool of GNN models to the time series domain, and the second part focuses the search on classification and forecasting applications.

The selection process of the papers followed the multi-stage approach described below:

1. **Database search**: the search query was submitted to each of the four databases, and all records were imported into a csv file.

2. **Duplicate removal**: duplicate records were identified and removed.

3. **Title and abstract screening**: the remaining records were screened by reading their titles and abstracts. Studies that at first sight did not meet the criteria were discarded.

4. **Full-text screening**: the full texts of the remaining papers were analyzed one by one, which led to a further assessment of eligibility.

5. **Data extraction**: relevant data were extracted from the included studies, and analyzed in order to better discuss the approach and present the most common datasets and models for each identified field.

A total of 473 records were identified, 188 from Scopus, 31 from IEEE, 104 from Web of Science, and 150 from ACM. A scheme of this selection process is sketched in Fig. 1. First, 142 duplicates were removed, then the titles and abstracts of the remaining 331 records were manually evaluated to select the pertinent papers. Among these, 170 were discarded because they were considered outside the scope of this review, and 5 were discarded because they were not in English. Hence, 156 records were included in the review. Next, Sec. 3 provides an overview of the selected publications.

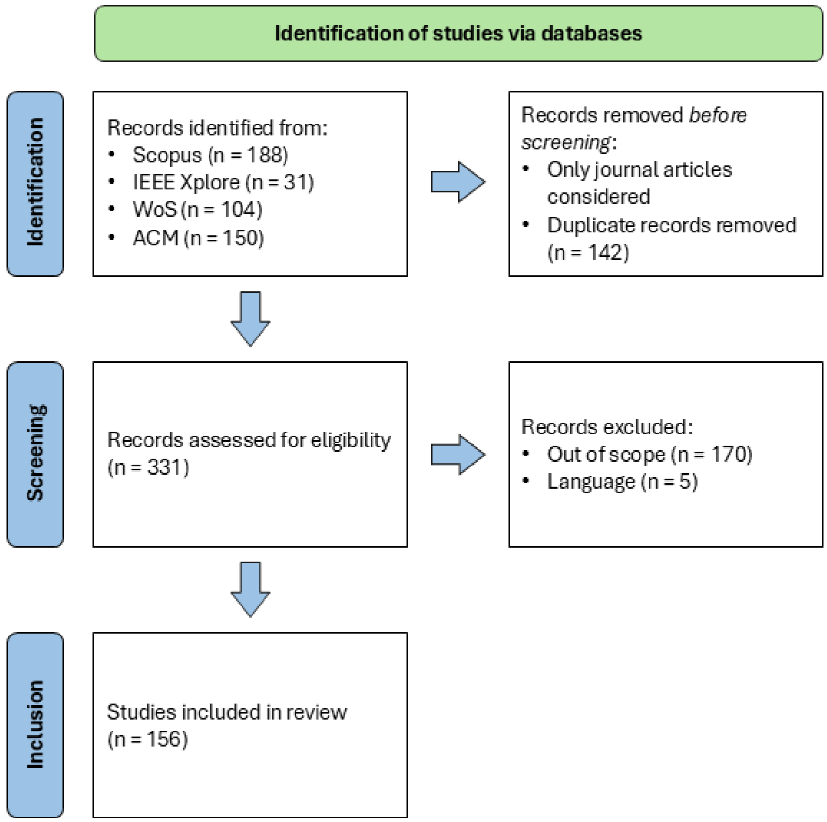


Figure 1: PRISMA flowchart to summarize the identification of the studies and the selection process, adapted from Ref. [145].

3 Overview of the publications

This section provides a comprehensive overview of the 156 selected journal articles. After their selection, the papers were grouped according to their domain of application, as better explained in the thematic analysis of Sec. 5. In the following, some bibliographic information about the reviewed articles is presented.

Fig. 2 illustrates the number of publications over time across different groups. A cumulative positive trend can be observed over time, reflecting an increasing interest in spatio-temporal GNN models across various fields, since 2020. The three most common groups that have seen the greatest increase in publications are "Environment", "Generic", and "Mobility". For more details, see also the group numerosity reported in Tab. 1.

An inspection of the publication sources indicates that 95 different journals have published articles on GNN models for time series forecasting or classification. Tab. 2 lists the 15 journals which contain the highest number of published papers. The diversity of the journals indicates a vast range of potential applications for spatio-temporal GNN models in different fields. This suggests that researchers often select journals based on the specific domain of application, allowing them to reach targeted audiences and contribute within their respective fields. Such diversity also underlines the interdisciplinary nature of GNNs research, as it spans multiple domains. In order to examine the degree of collaboration among researchers, a co-authorship network was generated by using the VOSviewer software [42]. Fig. 4

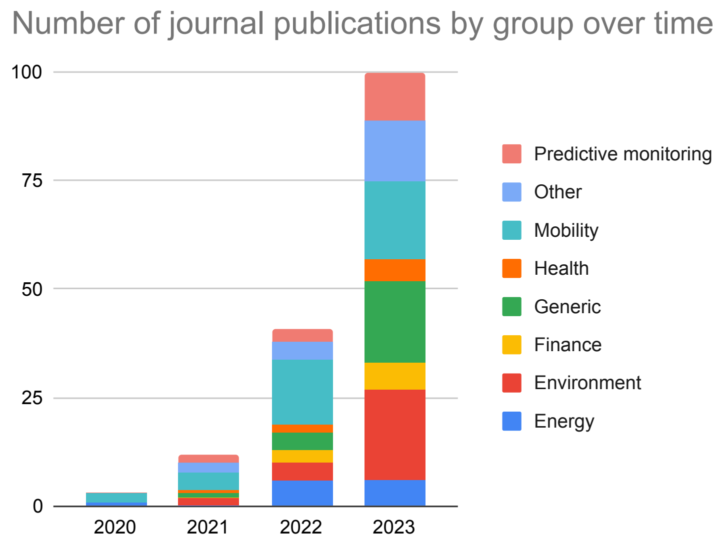


Figure 2: Number of journal publications over time across the different groups.

Table 1: Pivot table illustrating the number of publications by year and group.

Field / Year	2020	2021	2022	2023	**Total**
Energy	1		6	6	**13**
Environment		2	4	21	**27**
Finance			3	6	**9**
Generic		1	4	19	**24**
Health		1	2	5	**8**
Mobility	2	4	15	18	**39**
Other		2	4	14	**20**
Predictive monitoring		2	3	11	**16**
Total	**3**	**12**	**41**	**100**	**156**

illustrates authors as nodes and collaborations as connections, revealing some research clusters. Two of these clusters are enlarged and shown in Fig. 4b. In the figure, the color of the nodes is related to the average publication year of an author, so that the evolution of research groups over time can be evaluated. Two key observations can be made. First, the number of clusters suggests that there are many distinct research groups, indicating a high degree of fragmentation within the community. Second, the color of the nodes indicates that some groups were active only at the beginning and have since disappeared, while others have recently formed, as indicated by their yellow color. Some authors have various collaborations over time, as also shown in Fig. 4b.

Fig. 3 shows a pie chart of the distribution of corresponding authors among different countries. This visualization provides an overview of the global distribution of research activities. More than the 70% of the authors are affiliated with institutions in China.

Table 2: Top 15 journals with the highest number of published paper.

Journal	Number of papers
IEEE Access	7
ACM Transactions on Knowledge Discovery from Data	6
Applied Intelligence	6
IEEE Transactions on Instrumentation and Measurement	6
ACM Transactions on Intelligent Systems and Technology	5
Expert Systems with Applications	5
Sensors	4
Applied Energy	3
Applied Soft Computing	3
Energy	3
Engineering Applications of Artificial Intelligence	3
IEEE Transactions on Intelligent Transportation Systems	3
Information Sciences	3
International Journal of Data Science and Analytics	3
Knowledge-Based Systems	3

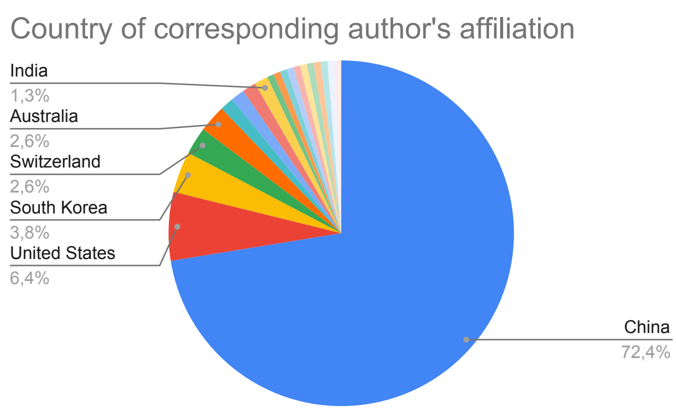
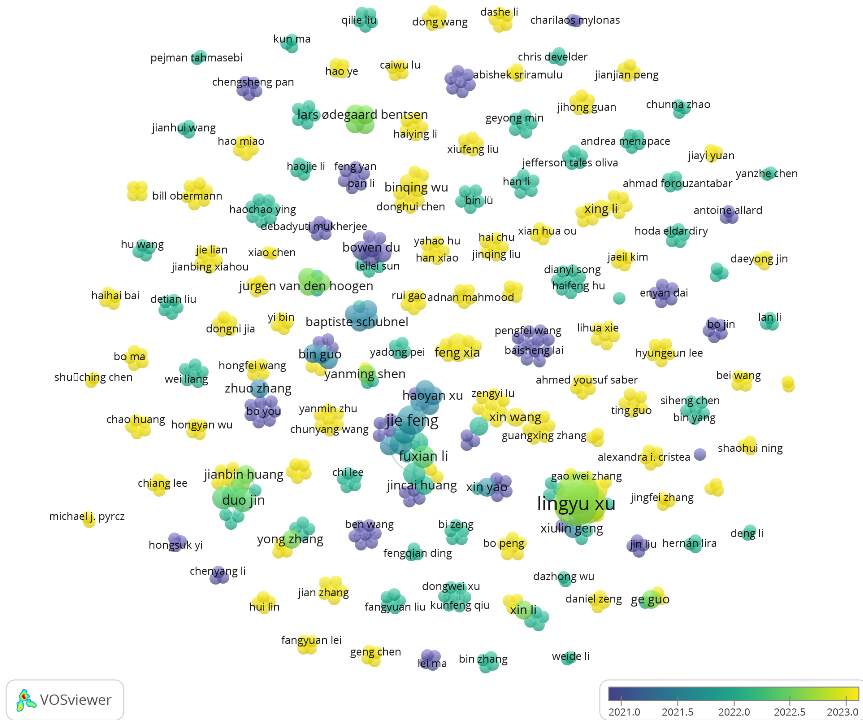
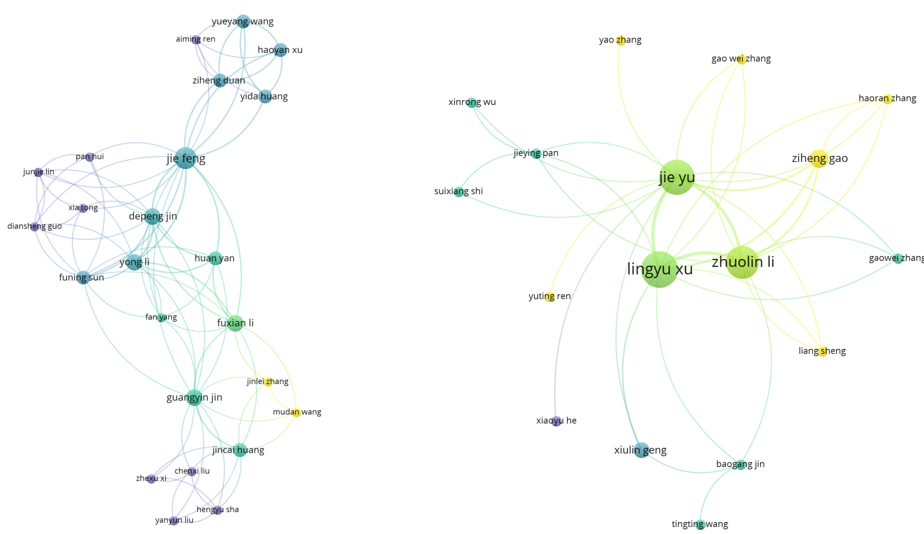


Figure 3: Pie chart of the distribution of corresponding authors in different countries.



(a) Visualization of the complete collaboration network.



(b) Zoom in on two different clusters.

Figure 4: Network of collaboration between researchers, created using VOSviewer software.

4 Graph neural networks

This section introduces some fundamental definitions and notions at the basis of the study of time series with spatio-temporal GNNs.

4.1 Definitions and notations

Definition 1 (Time series)**.** A time series is a sequence of data points indexed in time order (that here is assumed to be regularly sampled, i.e., equispaced). An equispaced univariate time series of length T is a sequence of scalar observations collected over time, denoted as $\vec{x}_t \in \mathbb{R}^T$. An equispaced multivariate time series of length T is a sequence of D-dimensional vector observations collected over time, denoted as $\vec{x}_t \in \mathbb{R}^{D\times T}$.

Definition 2 (Graph)**.** A graph $\mathcal{G}$ is a pair of finite sets $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V} = \{v_1, \ldots, v_n\}$ is a set of n nodes (also called vertices) and $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges. In an undirected graph each edge is an unordered pair of nodes $\{v_i, v_j\}$, while in a directed graph the edges have an orientation and correspond to ordered pairs (v_i, v_j). When an edge (v_i, v_j) or $\{v_i, v_j\}$ exists, the nodes v_i and v_j are called adjacent.

Definition 3 (Spatio-temporal graph)**.** A spatio-temporal graph is a 4-tuple $\mathcal{G} = (\mathcal{V}_t, \mathcal{E}_t, \mathcal{X}_t, \mathcal{T})$, where $\mathcal{T} = \{t_1, \ldots, t_T\}$ is a set of T timestamps t, $\mathcal{V}_t = \{v_1(t), \ldots, v_{n_t}(t)\}$ is a set of n_t nodes representing spatial entities at time t, $\mathcal{E}_t = \{e_1(t), \ldots, e_{m_t}(t)\}$ is a set of m_t edges representing the relationships between nodes at time t, $\mathcal{X}_t = \{x_{v_1}(t), \ldots, x_{v_{n_t}}(t)\} \cup \{r_{e_1}(t), \ldots, r_{e_{m_t}}(t)\}$ is a set of attributes associated with nodes and edges (x_{v_i} and r_{e_i} are respectively the attributes of node v_i and edge e_i, and can be either scalars of vectors) at time t. Notice that the sets of nodes and edges can change over time, as well as the set of attributes $\mathcal{X}_t$.

Definition 4 (Adjacency matrix)**.** The adjacency matrix $\mathcal{A}$ of a graph $\mathcal{G}$ with $|\mathcal{V}| = n$ nodes is a $n \times n$ square matrix, with $\mathcal{A}_{ij}$ specifying the number of connections from node v_i to node v_j for $i, j = 1, \ldots, n$. Here it is assumed that a graph cannot have more than one edge between any two nodes, so $\mathcal{A}_{ij}$ can only be 0 or 1 depending on whether there is a connection or not.

Definition 5 (Degree matrix)**.** The degree matrix $\mathcal{D}$ of a graph with $|\mathcal{V}| = n$ nodes is a diagonal matrix whose entries are given by the degree of each node, i.e., the number of edges attached to the node. In formulas, its diagonal elements are given by

$$\mathcal{D}_{ii} = \sum_j \mathcal{A}_{ij} \ . \tag{1}$$

4.2 Overview of graph neural networks

Given a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, a GNN model (not necessarily changing in time, i.e., spatio-temporal) aims to generate an embedding (i.e., a vector of real entries) for each node in the graph. An overall graph embedding consists of representing a graph into a possibly different-dimensional space while preserving its structural information.

The notion of GNN was initially proposed by Gori et al. in 2005 in Ref. [51] and by Scarselli et al. in 2009 in Ref. [160] as an architecture to implement a function that maps a graph $\mathcal{G}$ with n nodes into an m-dimensional Euclidean space. In Ref. [160] the target node's embedding was learned by first propagating forward at fixed weights neighbor information within the graph in an iterative manner, until a stable fixed point is reached (whose existence is guaranteed under certain assumptions by Banach's fixed point theorem), and then propagating errors on targets back across the graph. The calculation of node embeddings is in general quite complex, and over time many other methods have been developed. These methods are based on different architectures and sophisticated mechanisms. Based on these aggregating mechanisms, a taxonomy of GNN models with different classes has been defined. In this review, we adopt a taxonomy for the discussed spatio-temporal GNNs similar to the one proposed by Chen et al. in Ref. [18]. More details will be given in Subsec. 4.3.

4.3 Spatio-temporal GNNs and their taxonomy

The majority of research on spatio-temporal GNNs is focused on multivariate time series, as they can be naturally abstracted into spatio-temporal graphs, as depicted in Fig. 5. In this context, nodes correspond to different variables at a given time step, and edges represent relationships between variables. This spatio-temporal modeling assumes that the feature information of a node depends on both its

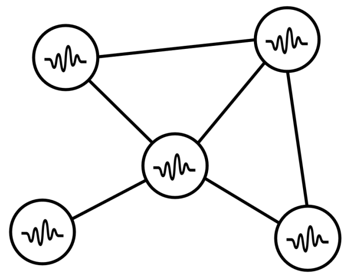


Figure 5: Representation of a spatio-temporal graph. Here, each node has a dynamic feature, given by the points of the time series.

own historical values and on the historical data from its neighboring nodes [223]. Once the the graph structure is given, information is propagated within it until the output is obtained, as better explained in the following.

When it comes to the development of a GNN model, there are two primary approaches: one that handles spatial and temporal substructures in separate blocks, and another that integrates and processes these two substructures together [223]. This is implemented by means of modules that are purely spatial, purely temporal, or hybrid combinations of the two. These modules are then organized into a series of blocks to create the final spatio-temporal GNN model.

In the taxonomy of spatio-temporal GNNs used in this review, the focus is exclusively on the description of the spatial module that propagates the information within the nodes at fixed time t (not explicitly included in the following equations for simplicity), which is in the reviewed literature a fundamental aspect that differentiates one GNN model from another. Based on the mechanism at the basis of the information propagation in the graph at a given time step, spatio-temporal GNNs can be further classified as recurrent GNNs, convolutional GNNs, and attentional GNNs, as explained in the following. These classes are not mutually exclusive, as some models may fit into hybrid categories. In addition, the classes are not fully exhaustive, as there may be models that do not align with any of the existing categories. However, for the purpose of this review, the taxonomy discussed above is sufficient.

Recurrent GNNs. Recurrent graph neural network modeling mainly includes the results of early studies on GNNs, where the node embeddings are generated by iteratively propagating neighbor information until a stable fixed point is reached. The iterative equation for the calculation of the embedding (or hidden state) of node u has the form

$$h_u^{(k)} = f\left(x_u, \{x_v, r_{(u,v)}, h_v^{(k-1)} \mid v \in \mathcal{N}(u)\}\right) , \tag{2}$$

where k is the index related to iteration, f is a parametric trainable function, x_u is the attribute associated to node u, $r_{(u,v)}$ is the weight of the edge (u, v) between the nodes u and v, $\mathcal{N}(v)$ denotes the neighborhood of node v, and the initial hidden states $h^{(0)}$ are usually randomly initialized. As detailed in Ref. [160], which introduced recurrent GNNs, to ensure the convergence of Eq. (2), it is necessary that the iterative function f is a contraction mapping.

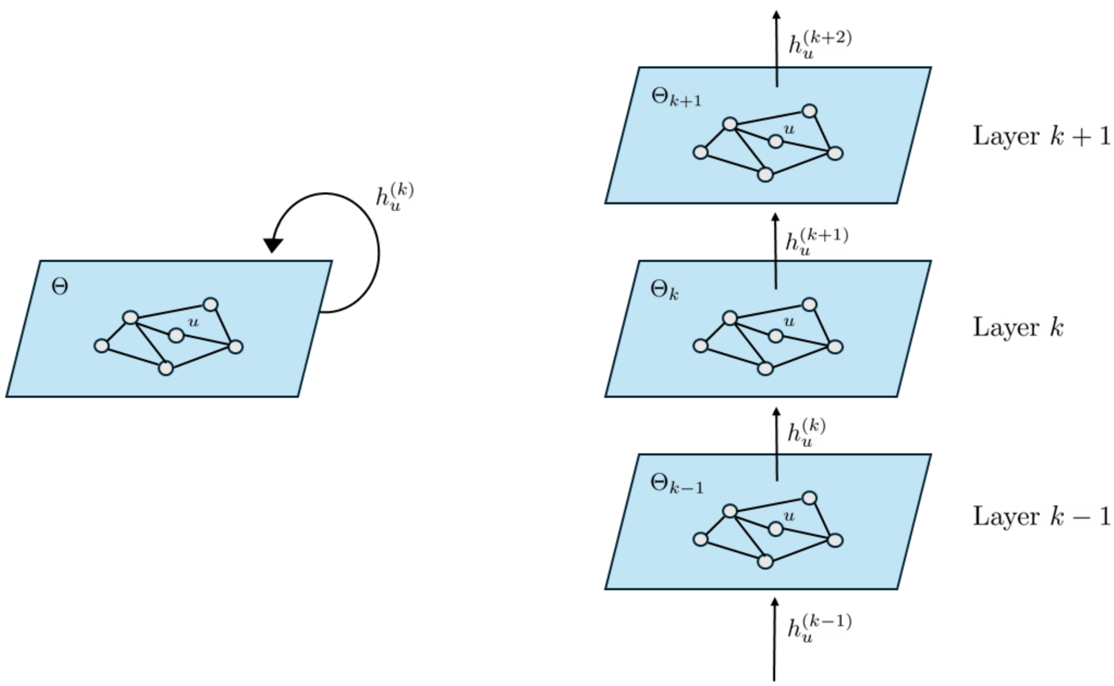
Convolutional GNNs. Convolutional graph neural networks are closely related to recurrent graph neural networks. They were at first introduced by Kipf and Welling in 2017 in Ref. [91]. Unlike recurrent GNNs, which apply the same iterative contraction mapping f until an equilibrium is reached, convolutional GNNs use different parameters at each updating step, by stacking multiple graph convolutional layers to extract the node embeddings [200].

A basic form for the equation for the k^{th} layer of a convolutional graph neural network with n

nodes is

$$H^{(k)} = f_k\left(\tilde{\mathcal{A}} H^{(k-1)} \Theta_{k-1}\right), \quad \tilde{\mathcal{A}} = \hat{\mathcal{D}}^{-\frac{1}{2}} \hat{\mathcal{A}} \hat{\mathcal{D}}^{-\frac{1}{2}}, \quad \hat{\mathcal{A}} = \mathcal{A} + I, \quad \hat{\mathcal{D}}_{ii} = \sum_j \hat{\mathcal{A}}_{ij}, \qquad H^{(0)} = X, \quad (3)$$

where f_k represents the convolutional operation performed at layer $k \in \{1, \ldots, K\}$, $\mathcal{A} \in \mathbb{R}^{n \times n}$ is the adjacency matrix, $I \in \mathbb{R}^{n \times n}$ is the identity matrix (used to add the self-loops in the adjacency matrix $\mathcal{A}$), $\hat{\mathcal{D}} \in \mathbb{R}^{n \times n}$ is the diagonal degree matrix associated to $\hat{\mathcal{A}}$, $H^{(k)} \in \mathbb{R}^{n \times d_k}$ are the d_k-dimensional node embeddings $h_v^{(k)}$ of the entire graph produced by the k^{th} layer, $X \in \mathbb{R}^{n \times d_0}$ is the collection of all node attributes x_v of the entire graph, and $\Theta_k \in \mathbb{R}^{d_{k-1} \times d_k}$ is a trainable weight matrix for the k^{th} layer [18]. The mechanism of node embedding generation from Eq. (3) is illustrated in Fig. 6b, where it is put in contrast with the mechanism of a recurrent GNNs, shown in Fig. 6a.



(a) Recurrent GNNs use the same graph recurrent layer in the iterative generation of the node embeddings. Here Θ represents the weights of the parametric trainable function f.

(b) Convolutional GNNs use different graph convolutional layers in the generation of the node embeddings.

Figure 6: Comparison of the node embedding generation mechanisms in a recurrent GNN (left panel) and a convolutional GNN (right panel).

Attentional GNNs. In attentional GNNs, the aggregation process uses the attention mechanism [178] to combine node features. The equations to compute the node embedding h_u of layer $k+1$ from the embeddings of layer k for each node u are

$$z_u^{(k)} = W_k h_u^{(k)}, \tag{4a}$$

$$\epsilon_{uv}^{(k)} = \text{LeakyReLU}\left(\vec{a}^{(k)\top}\left(z_u^{(k)} \,||\, z_v^{(k)}\right)\right), \tag{4b}$$

$$\alpha_{uv}^{(k)} = \frac{\exp\left(\epsilon_{uv}^{(k)}\right)}{\sum_{w \in \mathcal{N}(u)} \exp\left(\epsilon_{uw}^{(k)}\right)}, \tag{4c}$$

$$h_u^{(k+1)} = f\left(\sum_{v \in \mathcal{N}(u)} \alpha_{uv}^{(k)} z_v^{(k)}\right). \tag{4d}$$

Eq. (4a) represents a learnable linear transformation of the node embedding $h_u^{(k)}$ using the trainable weight matrix W_k of layer k. Eq. (4b) computes a pairwise masked attention score between nodes u and v by concatenating ($||$) the vectors $z_u^{(k)}$ and $z_v^{(k)}$, calculating a dot product with a learnable weight vector $\vec{a}^{\,(k)}$, and applying the LeakyReLU nonlinearity. The quantity ϵ_{uv} indicates the importance of the features of node v to node u. The term "masked" refers to the fact that ϵ_{uv} are only computed for neighboring nodes. Eq. (4c) normalizes the attention score through the softmax function in order to make the α_{uv} comparable across different nodes. Finally, Eq. (4d) computes the next layer embedding $h_u^{(k+1)}$ by aggregating the information in neighboring nodes, weighted by the attention scores [179]. Graph attention networks can also further use a multi-head attention mechanism to stabilize the learning process of self-attention. In practice, the node updating operation in graph attention networks is a generalization of the traditional averaging or max-pooling of neighboring nodes, which allows each node to compute a weighted average of its neighbors and identify the most relevant ones [12].

As anticipated, the taxonomy discussed so far focuses only on the propagation mechanisms of the spatial component. However, spatio-temporal GNNs typically consist of a stack of spatial, temporal, or hybrid modules, each one with distinct roles.

The spatial module is responsible for propagating information between nodes, thereby enabling the analysis of cross-sectional inter-dependencies between different variables. As previously explained in the description of the mechanisms underlying the taxonomy, the spatial module aggregates information starting from immediate neighboring nodes and extends it outward, thereby capturing also the influence of distant nodes. Noticeably, this spatial operation does not account in principle for temporal information. In contrast, the temporal module, often based on architectures such as LSTM, GRU, or self-attention, focuses on the evolution of data over time, independently from cross-sectional node interactions.

When these different modules are stacked together, spatial and temporal information end up to be used simultaneously, although they are processed in separate modules. This occurs because the computation of each node state is influenced by both spatial and temporal information. This combined approach allows the spatio-temporal GNN model to effectively capture at the same time both spatial relationships and temporal dynamics.

4.4 Determination of the graph structure

A crucial issue when dealing with spatio-temporal GNNs for time series problems is the determination of the graph structure, i.e. the connectivity of the nodes. Namely, some time series datasets come by nature with a pre-defined graph structure (e.g., road network), while some others do not. When a natural pre-defined graph structure is available, it helps the model to better capture the underlying dynamics of the system. When it is not directly available, it must be in some way defined by the user (based on domain knowledge or some metrics), determined by some algorithm (such as visibility graphs [224], [96], [183]), or learned by the model itself.

Once the graph structure has been determined, it is necessary to define the weighted graph adjacency matrix, which is a generalization of the graph adjacency matrix whose entries are given by the edge weights of the graph. The edge weights can be defined *a priori* by the user, or again, learned by the model itself based on a pre-defined architecture. In the first case, the edge weights are assigned based on some pre-defined metrics or criteria chosen by the user (e.g., spatial distance between the sites or similarity measures). In the latter case, the weights are continuously adjusted throughout training as the model learns from the data.

Each section of the following thematic analysis examines which approach is prevalent.

5 Thematic analysis

This section explores the diverse applications of GNN models in different groups. As said, the selected journal papers are divided in groups according to the application domain. The goal is to provide an overview of the various empirical studies, the most common approaches, and the results obtained for different applications.

In each subsection of the following thematic analysis, a list of the benchmark models that appear in the selected journal papers will be provided. They will be classified as: mathematical and statistical models coming from Econometrics, traditional machine learning models, and GNN-based models. As for mathematical and statistical models, they generate forecasts by analyzing a limited amount of data, and they usually struggle with cross-sectional large-scale and temporal long-term dependencies. Traditional machine learning models use more complex architectures, mainly neural networks, but they are not necessarily able to capture intricate spatio-temporal dependencies within the data. GNN-based models instead, attempt to represent these complex dependencies using various techniques, resulting in better, though not perfect, accuracy. In addition, information on the most common datasets will be given, along with the best results reported in the literature. All results presented in the tables of this SLR are taken directly from the tables of the selected papers.

The groups of papers are presented in alphabetical order, with the exception of the "Generic" applications group (which cannot be directly attributed to a specific case study) and the "Other topics" group (focusing on specific problems of other disciplines). In subsections with a large number of papers and high homogeneity of the datasets, more precise comparisons of the results and in-depth analyses will be conducted.

5.1 Energy

The first group of papers is "Energy" (with 13 out of 156 papers), which includes all the studies related to energy systems. In particular, it includes research on electricity load, energy consumption, and power generation forecasting. This is somehow connected to the "Environment" subsection (Subsec. 5.2). Indeed, green energy sources are associated with environmental phenomena such as wind speed and solar radiation inflow. However, this subsection focuses on energy applications, whereas Subsec. 5.2 refers to the study of environmental data that may or may not be related to energy applications. Wind speed forecasting, for instance, is connected to wind power generation due to the cubic relationship between wind speed and wind power [7]. However, wind speed forecasting may also be of interest for other reasons, and thus it is included in the more general Subsec. 5.2.

5.1.1 Overview

Energy forecasting is crucial for electricity power grid stability and operational efficiency. Accurate load and generation forecasts ensure that supply meets real-time demand, preventing outages and instability, and maintaining a reliable supply of power. In addition, effective forecasting allows for optimal scheduling of power plants and energy resources, reducing operational costs and improving overall system efficiency. The majority of econometric and machine learning models tend to focus on time series from a single site or consider multiple sites without explicitly capturing the relationships between them. GNN models may be an innovative and effective approach to addressing energy related problems.

An overview of the selected papers reveals a noticeable interest in the application of GNNs in the energy field since 2022. The most frequently studied fields include forecasting of wind ([63], [219], [105]) and solar power ([34], [167], [168], [155]), which are renewable energy sources characterized by their intermittency. The two most popular journals among the selected papers are *Applied Energy* by Elsevier, and *Frontiers in Energy Research* by Frontiers Media SA. The majority of the corresponding authors are affiliated with institutions in China and in the United States.

5.1.2 Datasets

The study of the selected papers in the "Energy" group suggests that there are no particularly common or widely recognized benchmark datasets. Indeed, researchers often focus on specific datasets, typically collected within the university campus or in the country where they are located. For the same reason, the links to these datasets are not always available. In Tab. 3 are listed the links to the public datasets mentioned in the papers.

Table 3: List of public datasets in the "Energy" group and their corresponding links.

Dataset	Used by	Link
Danish smart heat meters	[195]	https://doi.org/10.5281/zenodo.6563114
DKA Solar Centre	[34]	https://dkasolarcentre.com.au/

IEEE bus systems	[240]	https://doi.org/10.1109/UPEC.2015.7339813 (source paper)
JERICHO-E-usage	[195]	https://doi.org/10.6084/m9.figshare.c.5245457.v1
NREL	[63], [168], [219]	https://www.nrel.gov/
OPSD	[229]	https://open-power-system-data.org/
PV Switzerland	[167], [168]	https://doi.org/10.1109/IJCNN48605.2020.9207573 (source paper)
UMass Smart* Dataset	[191]	https://traces.cs.umass.edu/index.php/Smart/Smart

Three of the selected papers ([63], [168], [219]) use data from the National Renewable Energy Laboratory (NREL), a national laboratory of the U.S. Department of Energy (https://www.nrel.gov/). Additional datasets were used for exogenous weather variables and satellite imagery (such as Himawari-8, available at https://www.data.jma.go.jp/mscweb/en/himawari89/space_segment/spsg_sample.html in Ref. [34]), but they are of course highly dependent on the location of the study. The data granularity ranges from 1 minute to 1 hour, and the forecasting horizon from tens of minutes to days. They depend on the dataset, the domain of application, and the purpose of the forecast. Most datasets require pre-processing, including missing data interpolation, normalization, and satellite image processing.

5.1.3 Proposed models

As for the taxonomy of the proposed GNN models, 8 out of 13 papers use a convolutional GNN, and the other 5 use an attentional GNN. Regarding the graph structure, the papers typically provide only a brief description. For example, it is rarely highlighted whether the graph structure is static or dynamic, and the way in which it is constructed is often described summarily. In some papers, the graph structure reflects the geographic location of the elements (e.g., wind or solar power plants, as in Refs. [219] and [155]), whereas in others it is based on the correlation or similarity between time series (as in Ref. [34]). In some studies, a pre-defined structure is imposed and the weighted adjacency matrix is learned directly from the model, often using the attention mechanism as in Ref. [168].

The most common loss function used to train the models is the MSE. Many papers mention the programming languages Python and Matlab, and few of them mention the Python libraries PyTorch [150] and TensorFlow [1] for the implementation of the GNN model. In this group, only Ref. [191] provides the link to the source code of the proposed residential load forecasting with multiple correlation temporal graph neural networks (RLF-MGNN) model (available at https://codeocean.com/capsule/9294192/tree/v1).

5.1.4 Benchmark models

Tab. 4 lists the benchmark models used in the "Energy" group by at least two papers included in this review.

Table 4: List of benchmark models in the "Energy" group divided per category.

Category	Model	Used by
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	[195], [229], [168], [68]
Classical machine learning methods	Bidirectional long-short term memory network (BiLSTM) [52]	[195], [34]
	Convolutional neural network (CNN)	[195], [45], [167], [168]

	Hybrid convolutional neural network and long-short term memory network (CNN-LSTM)	[195], [191]
	Encoder-decorer architectures (ED)	[195], [34], [167], [168]
	Feed-forward neural network (FNN)	[195], [45], [34], [68], [105]
	Gated recurrent unit (GRU)	[195], [68]
	Informer [243]	[195], [229]
	k-nearest neighbors (KNN)	[45], [219]
	Long-short term memory network (LSTM)	[195], [229], [34], [63], [240], [219]
	Recurrent neural network (RNN)	[229], [191], [34], [63]
	Support vector regression (SVR)	[167], [168], [219], [105]
	Transformer [178]	[229], [34]
GNN methods	Spatio-temporal autoregressive model (ST-AR) [16]	[167], [168]

The majority of the papers only use classical machine learning benchmarks. Some papers use simple mathematical and statistical models, such as linear regression (that we incorporated into ARIMA) or historical average. Only few papers use other GNN-based models as benchmarks, and there are no common benchmarks among them. This is due to the fact that this field has not been extensively explored in the past, and only a very limited number of GNN models have been specifically developed for energy forecasting.

5.1.5 Results

In all the papers, the authors claim that the proposed GNN model outperforms the benchmarks. The most common error metrics are the MAE, the RMSE, and the Normalized Root Mean Square Error (NRMSE).

It is not possible to compare the accuracy of the discussed models because there are no common benchmark datasets. The only two papers that study the same dataset are written by the same authors (Refs. [167] and [168]), and their most recent paper includes a comparison with the models proposed in the first one.

5.2 Environment

The group "Environment" includes a significant number of the selected papers (27 out of 156), which suggests a considerable research interest on the application of GNNs in this field. However, this group is highly fragmented, as it includes a large number of subdomains and applications, all related to the study of environmental data.

5.2.1 Overview

The group of environmental studies is broad and includes several disciplines such as physics, climatology, oceanography, and atmospheric science. The breadth of the group is reflected in the number of case studies presented in the selected papers, which cover air quality prediction (in terms of $PM_{2.5}$ concentration), sea temperature, wind speed, and other applications. Forecasting these quantities can be useful for several reasons. For instance, predicting wind speed or rainfall can assist in anticipating some extreme weather phenomena, and is also related to the prediction of green energy outputs. For example, in Refs. [7] and [8] the authors estimate the wind power forecasting error obtained by using wind speed forecasting models. As another example, predicting sea surface temperature can be useful for weather forecasting, fishing directions, and disaster warnings [209]. Moreover, monitoring and forecasting environmental data are crucial for evaluating the impact of human activities on the environment and tracking the progression of climate change.

The methods for forecasting environmental data are typically categorized as numerical models, statistical models, and machine learning methods. Numerical methods are based on atmospheric models, and are designed to quantify the interaction of different atmospheric variables. The accuracy of these models depends on the availability of data, and the mathematical simulations to get the forecasts may take days or even weeks, thus limiting the ability to make good short-term forecasts. Linear statistical methods leverage long-term dependencies in the recorded data by using regression-like models. However, they cannot capture non-linear relationships in the dataset, which limits their power. Machine learning models, on the other hand, are often a generalization of linear statistical methods that can capture more complex and non-linear relationships in the data.

An overview of the selected papers reveals that there has been a rapid increase in interest in the field among the GNN research community, and more than 20 of the selected papers were published in 2023. The most investigated subjects are sea temperature ([209], [87], [147], [47], [187], [173], [164]), wind speed ([7], [157], [8], [49], [46], [40]), and $PM_{2.5}$ concentration forecasting ([131], [171], [110], [139], [86], [151]). All the selected papers are published in different journals, with the exception of the *Engineering Applications of Artificial Intelligence* by Elsevier, which has published two of the papers. The majority of the corresponding authors are affiliated with institutions in China.

5.2.2 Datasets

The analysis of the selected papers shows that in this group of papers there is no reference benchmark dataset. The publicly available datasets cited in the papers are listed in Tab. 5.

Table 5: List of public datasets in the "Environment" group and their corresponding links.

Dataset	Used by	Link
AgroData-10	[209]	https://www.aoml.noaa.gov/phod/argo
CCMP wind data	[157], [49], [46]	http://data.remss.com
China Environmental Monitoring Station $PM_{2.5}$	[131], [151]	https://www.cnemc.cn/
China National Urban Air Quality	[22], [39]	https://github.com/Friger/GAGNN
Copernicus 3D thermohaline data	[147]	https://resources.marine.copernicus.eu/products
ECMWF East China Sea	[152]	https://github.com/Boltzxuann/GIPMN/tree/dataset
ECMWF South and East China Sea	[236]	http://apps.ecmwf.int/datasets/data/interim-full-daily
KnowAir	[139]	https://doi.org/10.1145/3397536.3422208 (source paper)
Korean Peninsula sea data	[87]	https://www.nifs.go.kr/risa/main.risa
NOAA sea datasets	[209], [47], [187], [40], [164]	https://www.ndbc.noaa.gov/
Norwegian offshore wind	[7], [8]	https://frost.met.no/index.html
Taiwan air quality dataset	[171]	https://data.gov.tw/en
UrbanAir	[139]	https://doi.org/10.1016/j.chemosphere.2018.12.128 (source paper)
US EPA $PM_{2.5}$	[22], [110]	https://aqs.epa.gov/aqsweb/airdata/download_files.html

Five of the selected papers ([209], [47], [187], [40], [164]) use National Oceanic and Atmospheric Administration (NOAA) sea datasets (https://www.noaa.gov/) from the U.S. Department of Commerce (US DOC). The US DOC website permits users to download daily, weekly and monthly mean optimum interpolation sea surface temperature (OISST) data from September 1981 for many geographical locations. In over half of the papers, exogenous variables are incorporated into the model.

These include weather data (e.g., humidity, rainfall, pressure, temperature, wind) and, in the case of $PM_{2.5}$ concentration forecasting, other pollutants (e.g., CO, NO_2, O_3, PM_{10}, SO_2).

The data granularity ranges from 1 minute to 1 month, depending on the case study, and the forecasting horizon from 10 minutes to 240 days. Most datasets require some pre-processing, including interpolation of missing data, removal of outliers and normalization.

5.2.3 Proposed models

Regarding the taxonomy of the proposed GNN models, the majority of papers present convolutional GNN (17 out of 27 papers), followed by 6 attentional GNNs and 3 hybrid architectures. The description in one paper (Ref. [39]), however, does not specify the classification of its model within the proposed taxonomy. As for the graph structure, not all of the papers describe it with sufficient precision, and some of them are vague about the graph construction and its static or dynamic nature. In almost half of the papers, the edge weights are learned directly from the model, often using the graph attention mechanism. When the graph structure is defined manually, the most popular criterion is the spatial distance between the sites (d), even in its exponential (e^{-d}) or inverse proportion ($1/d$) formulation. Finally, there are a few papers where more than one graph structure is fused together in order to capture more complex dynamics, as in Ref. [131].

Not all papers specify the loss function used to train the models. Among those that do, MAE and MSE are used in roughly equal proportions. Many papers mention the programming language Python and the library PyTorch for the implementation of the models. Few papers also provide a link to the source code for the proposed model, as shown in Tab. 6.

Table 6: List of source codes of the "Environment" models in the review.

Model	Link
Group-aware graph neural network (GAGNN) [22]	https://github.com/Friger/GAGNN
Gridded information propagation and mixing network (GIPMN) [152]	https://github.com/Boltzxuann/GIPMN/tree/dataset
Hierarchical graph recurrent network (HiGRN) [209]	https://github.com/Neoyanghc/HiGRN
Spatio-temporal FFTransformer (ST-FFTransformer) [7]	https://github.com/LarsBentsen/FFTransformer

5.2.4 Benchmark models

Tab. 7 presents the benchmark models employed in the "Environment" group by at least two articles examined in this review.

Table 7: List of benchmark models in the "Environment" group divided per category.

Category	Model	Used by
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	[209], [87], [8], [126]
	Historical average (HA)	[171], [139], [209], [126]
	Naive	[7], [8]
	Vector autoregression (VAR)	[209], [8], [126]
Classical machine learning methods	Bidirectional long-short term memory network (BiLSTM) [52]	[87], [40]
	Combined FC-LSTM and convolution neural network (CFCC-LSTM) [213]	[147], [187]
	Hybrid convolutional neural network and gated recurrent unit (CGRU) [206]	[157], [49], [46]
	Convolutional neural network (CNN)	[101], [40]

	Hybrid convolutional neural network and long-short term memory network (CNN-LSTM)	[110], [173]
	Convolutional long-short term memory network (ConvLSTM) [165]	[209], [173]
	Feed-forward neural network (FNN)	[131], [86], [126]
	Gated recurrent unit encoder–decoder (GED) [204]	[47], [187], [164]
	Gated recurrent unit (GRU)	[131], [139], [86], [151], [126], [6], [40]
	Informer [243]	[101], [164]
	Long-short term memory network (LSTM)	[22], [131], [171], [110], [39], [139], [86], [151], [209], [101], [236], [87], [147], [47], [126], [187], [6], [40], [164]
	Predictive deep convolutional neural network (PDCNN) [245]	[157], [49]
	Support vector regression (SVR)	[171], [139], [147], [47], [126]
	Temporal convolutional network (TCN) [5]	[139], [101]
	Temporal pattern attention long-short term memory network (TPA-LSTM) [166]	[139], [157], [236], [147], [49], [46]
	Transformer [178]	[101], [87]
	Hybrid wavelet random forest and deep belief network (Wavelet-DBN-RF)	[157], [49], [46]
	Extreme gradient boosting (XGBoost)	[22], [131], [39], [40]
GNN methods	Deeper graph convolutional network (DeeperGCN) [104]	[22], [39]
	Graph convolutional neural network and long-short term memory (GC-LSTM) [154]	[22], [131], [39], [139], [86]
	Graph convolutional network (GCN)	[126], [173]
	Graph WaveNet (GWN) [202]	[22], [139], [46], [164]
	Hierarchical graph convolution network (HGCN) [56]	[22], [209]
	Multivariate time series forecasting with graph neural network (MTGNN) [201]	[139], [236], [46]
	Multi long-short term memory network (Multi-LSTM) [50]	[157], [49], [46]
	Superposition graph neural network (SGNN) [219]	[157], [49]
	Spatio-temporal graph convolutional network (STGCN) [216]	[171], [139], [209], [147], [164]
	Spatio-temporal correlation graph neural network (STGN) [49]	[157], [46]
	Spatio-Temporal U-Network (ST-UNet) [217]	[22], [39]
	Temporal graph convolutional network (T-GCN) [239]	[139], [101], [147]

The majority of the benchmarks used fall within the category of classical machine learning, although there are several GNN benchmarks as well. The two most common benchmark models are LSTM and GRU. These models are widely used by environmental data forecasters due to their ability to capture temporal dependencies, and they are considered a reliable benchmark in the field. As for GNN models, the most common benckmarks are the graph convolutional neural network and long-short term memory (GC-LSTM) [154] (which appears only in quality air forecasting problems) and spatio-temporal graph convolutional network (STGCN) [216]. The GC-LSTM is a model that integrates graph convolutional networks and long-short-term memory networks, proposed by Qi et al. in 2019 to forecast the spatio-temporal variation of $PM_{2.5}$ concentration. The STGCN model instead was proposed in the traffic domain by Yu et al. in 2018. This model is composed of two spatio-temporal convolutional blocks and a fully-connected output layer. Each convolutional block contains two temporal gated convolution layers and one spatial graph convolution layer in the middle. The code for the STGCN model is available at https://github.com/VeritasYin/STGCN_IJCAI-18. Finally, it is important to point out that the multivariate time series forecasting with graph neural network (MTGNN) model proposed by Wu et al. in 2020 in Ref. [201] is often the second-best performing model in the papers using it, thus it deserves more attention and further investigation in future research.

5.2.5 Results

In each paper, the proposed model significantly improves on the benchmarks. The accuracy of the models is measured in terms of MAE, RMSE, and MAPE. Among the papers, there is a high diversity in the choice of the proposed datasets. However, there are two sets of papers using the same dataset, whose results can be compared.

The first dataset is the CCMP wind speed dataset (available at http://data.remss.com), which contains 3,942 geographical grid points from the east and southeast sea areas of China. The three papers using it ([157], [49], [46]) select 120 points from the area and use data records from January 2010 to April 2019 at 6 hours intervals, with a total of 13,624 samples at each node, for 10 different forecasting horizons. All papers present results for the complete set of 120 nodes and a subset of nodes. However, since their results are similar, only the average results for all the 120 nodes are reported in Tab. 8 for the sake of simplicity.

Table 8: Comparison of the average accuracy of the different models on the CCMP wind speed dataset for time horizons from 6 hours to 7 days ahead, expressed in terms of MAE and RMSE. The smallest errors are underlined. Numbers from the papers.

Model	Metrics	6 h	12 h	18 h	1 d	2 d	3 d	4 d	5 d	6 d	7 d
CGRU	MAE	1.658	1.795	1.937	2.038	2.290	2.401	2.478	2.525	2.556	2.594
	RMSE	2.100	2.277	2.461	2.594	2.911	3.042	3.141	3.198	3.245	3.285
DAGLN [157]	MAE	1.068	1.219	1.346	1.443	1.716	1.852	1.935	1.984	2.019	2.067
	RMSE	1.423	1.625	1.793	1.917	2.255	2.428	2.512	2.570	2.607	2.656
DASTGN [46]	MAE	1.039	1.184	1.297	1.387	1.662	1.806	1.900	1.945	1.995	2.028
	RMSE	1.384	1.572	1.721	1.829	2.170	2.338	2.449	2.498	2.554	2.600
DLinear	MAE	1.145	1.306	1.432	1.528	1.798	1.937	2.022	2.080	2.124	2.155
	RMSE	1.528	1.745	1.913	2.037	2.366	2.512	2.604	2.666	2.713	2.748
EMD-SVRCKH	MAE	1.111	1.311	1.432	1.526	1.788	1.919	1.998	2.051	2.090	2.119
	RMSE	1.489	1.755	1.909	2.027	2.344	2.495	2.587	2.650	2.695	2.730
Graph WaveNet	MAE	1.101	1.265	1.386	1.487	1.762	1.901	1.951	1.992	2.089	2.124
	RMSE	1.467	1.685	1.852	1.982	2.304	2.466	2.554	2.582	2.684	2.717
Historical Inertia	MAE	1.139	1.301	1.405	1.511	1.773	1.912	2.007	2.081	2.109	2.114
	RMSE	1.494	1.704	1.843	1.977	2.304	2.467	2.571	2.637	2.678	2.687
MTGNN	MAE	1.091	1.237	1.351	1.454	1.724	1.864	1.935	1.990	2.036	2.059
	RMSE	1.454	1.650	1.801	1.936	2.267	2.436	2.515	2.579	2.632	2.657
Multi LSTMs	MAE	1.312	1.645	1.914	2.129	2.610	2.748	2.793	2.818	2.842	2.867
	RMSE	1.663	2.079	2.415	2.679	3.257	3.420	3.477	3.510	3.540	3.573
PDCNN	MAE	2.025	2.026	2.385	2.551	2.959	3.011	3.012	2.971	2.918	2.877
	RMSE	2.561	2.562	3.033	3.243	3.750	3.824	3.833	3.789	3.727	3.675

SGNN	MAE	2.542	2.562	2.573	2.578	2.583	2.618	2.666	2.695	2.712	2.716
	RMSE	3.222	3.246	3.264	3.270	3.275	3.328	3.392	3.431	3.453	3.458
STGN [49]	MAE	1.084	1.281	1.407	1.523	1.809	1.942	2.046	2.073	2.137	2.189
	RMSE	1.430	1.697	1.863	2.013	2.358	2.514	2.631	2.649	2.717	2.771
TPA-LSTM	MAE	1.203	1.552	1.803	1.984	2.432	2.667	2.836	2.959	3.027	3.045
	RMSE	1.562	1.997	2.319	2.544	3.082	3.383	3.598	3.745	3.825	3.842
Wavelet-DBN-RF	MAE	1.451	1.597	1.749	1.836	2.087	2.162	2.200	2.217	2.232	2.243
	RMSE	1.855	2.038	2.226	2.328	2.617	2.703	2.744	2.766	2.788	2.798

For all the time horizons, the most recent dynamic adaptive spatio-temporal graph neural network (DASTGN) model [46] has the highest accuracy. Other two well performing models are the data-based adaptive graph learning network (DAGLN) [157] and the multivariate time series forecasting with graph neural network (MTGNN) [201].

The second dataset shared by two papers ([22], [39]) is the one of China National Urban Air Quality (available at https://github.com/Friger/GAGNN). It contains air quality index data (AQI) of 209 cities, collected from January 2017 to April 2019 at 1 hour granularity, for a total of 20,370 samples. Both the papers also integrate exogenous weather variables (humidity, wind direction, wind speed, rainfall, air pressure, temperature, and visibility) collected from Envicloud (http://www.envicloud.cn /). The average accuracy of the models used in the two papers is compared in Tab. 9.

Table 9: Comparison of the average accuracy of the different models on the Chinese AQI dataset for time horizons from 1 to 6 hours ahead, expressed in terms of MAE and RMSE. The smallest errors are underlined. Numbers from the papers.

Model	Metrics	1h	2h	3h	4h	5h	6h
AirFormer	MAE	5.95	9.31	11.87	13.87	15.52	16.95
	RMSE	11.49	17.23	21.32	24.31	26.72	28.71
DeeperGCN	MAE	6.54	9.74	11.77	13.40	15.29	16.41
	RMSE	13.67	18.93	21.14	23.83	26.25	28.02
FGA	MAE	5.87	9.14	11.71	13.75	15.42	16.80
	RMSE	11.36	17.01	21.05	24.09	26.55	28.52
GAGNN [22]	MAE	5.56	8.59	10.80	12.52	13.91	15.10
	RMSE	10.81	16.17	19.84	22.51	24.63	26.37
GC-LSTM	MAE	5.95	9.16	11.58	13.46	15.00	16.31
	RMSE	11.91	16.98	20.82	23.69	25.97	27.82
GWNet	MAE	5.76	9.64	12.79	15.30	17.28	18.81
	RMSE	11.27	17.57	22.31	25.75	28.52	30.48
HGCN	MAE	5.70	9.09	11.73	13.84	15.55	16.95
	RMSE	11.18	17.09	21.33	24.52	26.99	28.94
HighAir	MAE	5.50	8.52	10.81	12.50	14.00	15.09
	RMSE	10.80	16.10	19.85	22.70	24.91	26.40
INNGNN [39]	MAE	5.48	8.49	10.67	12.34	13.72	14.91
	RMSE	10.70	16.03	19.66	22.29	24.37	26.11
LSTM	MAE	6.50	10.26	13.18	15.52	17.40	18.91
	RMSE	13.85	19.26	23.52	26.83	29.46	31.55
MegaCRN	MAE	5.38	8.76	10.80	12.73	14.46	16.03
	RMSE	10.64	16.46	19.92	22.82	25.45	27.60
SHARE	MAE	5.84	9.07	11.49	13.35	14.74	15.79
	RMSE	11.27	16.84	20.77	23.60	25.80	27.38

ST-UNet	MAE	5.95	9.30	11.58	13.38	14.82	16.02
	RMSE	11.74	18.01	21.34	23.90	25.94	27.64
XGBoost	MAE	6.85	10.89	13.99	16.27	18.14	19.56
	RMSE	14.25	19.80	24.72	28.14	30.63	33.44

The hybrid interpretable neural network and graph neural network model (INNGNN) [39] is the most accurate model for all time horizons except 1 hour, where it is beaten by the meta-graph convolutional recurrent network model (MegaCRN) [74]. The authors attribute this result to the fact that in the short term the AQI is strongly influenced by nearby cities, and the MegaCRN model is more focused on local features.

5.3 Finance

"Finance" is another emerging field of study, though not yet widely explored, with 9 out of 156 selected papers. The difficulty of predicting financial data is a well-established fact. This is due to the inherently complex nature of markets, the influence of geopolitical events on them, and the unpredictable behavior of humans which is often irrational and difficult to predict. This complexity makes financial time series highly volatile, and accurate forecasts and data modeling are essential to develop effective trading strategies. GNNs are taken into consideration to model the inter-dependencies between variables together with series dynamics.

5.3.1 Overview

The "Finance" group is relatively narrow, in part due to the limited number of published papers. The majority of studies are concentrated on stock price prediction ([69], [149], [176], [186], [174]), with the aim of forecasting the future trend of the price of a company. Sometimes the stock prediction problem is seen as a classification task. Indeed, due to the stochastic nature and volatility of financial markets, predicting price movements ("up", "neutral", "down") can be more feasible than accurately forecasting specific prices. For example, assuming a daily granularity, a rise ("up") can be considered to occur when the next trading day's closing price (p_t) is at least 0.55% higher than the previous day's closing price (p_{t-1}), whereas if p_t is more than 0.50% lower than p_{t-1}, the price movement can be classified as a "down". Otherwise, it is classified as "neutral". All the selected papers addressing stock prices approach the problem from a classification perspective. Another distinctive aspect in this group of papers is that researchers usually also evaluate how their predictions affect the stability of investment returns over a specified period. This is commonly done through trading simulations in the test set, evaluated with metrics such as the Sharpe ratio and overall returns. These simulations require modeling rather than forecasting.

An examination of the selected papers indicates an interest in the application of GNNs in Finance from 2022. Two of the papers were published in *IEEE Access* by IEEE, while the remaining ones appeared in various other journals. Most of the corresponding authors are affiliated with academic institutions in China.

5.3.2 Datasets

The number of datasets in this group is limited. The links to the public datasets referenced in the selected papers are listed in Tab. 10.

Table 10: List of public datasets in the "Finance" group and their corresponding links.

Dataset	Used by	Link
China A-Shares	[186], [174], [28]	https://finance.sina.com.cn/stock
CSI 100 index	[176]	https://tushare.pro/
CSI 300 index	[69], [176]	https://global.csmar.com/
S&P 100 index	[176]	https://finance.yahoo.com/

S&P 500 index	[69]	https://finance.yahoo.com/
Russell 1K index	[176]	https://finance.yahoo.com/
Russell 3K index	[176]	https://finance.yahoo.com/

All the listed datasets represent collections of stock indices. The most common datasets include the China Securities Index (CSI), the 100 and 500 Standard and Poor's (S&P) indices, and the 100 and 300 China A-Shares indices. Many studies also include exogenous data, such as other market data, events, and news. As for the news, they can be processed by some language model like BERT (as in Refs. [69] and [28]). Most of the data have a granularity of 1 day (which is typical of financial data), and the forecasting horizon is also generally 1 day. Only one of the selected papers (Ref. [176]) analyses also longer time horizons for stock forecasting. As for pre-processing, half of the selected papers use normalization techniques, including min-max normalization, Z-score normalization, and logarithmic normalization.

5.3.3 Proposed models

In terms of the taxonomy of the proposed GNN models, 5 out of 9 papers utilize attentional GNNs, while the other 4 papers employ convolutional GNNs. As for the graph structure, some papers use models which learn the graph structure themselves ([176], [111]), while some others defines it a priori based on the relationships between companies and stocks ([186], [72], [214]).

Since the majority of papers deal with a stock movement classification problem, the most common loss function is the cross entropy. The majority of the papers explicitly indicate that Python is the programming language utilized, with nearly half employing PyTorch and a few utilizing TensorFlow. Only Ref. [186] provides a link to the source code of the proposed knowledge graph and graph convolution neural network (KG-GCN) model, available at https://github.com/Gjl12321/KG_GCN_Stock_Price_Trend_Prediction_System.

5.3.4 Benchmark models

Tab. 11 displays the benchmark models utilized in the "Finance" group by a minimum of two of the selected papers.

Table 11: List of benchmark models in the "Finance" group divided per category.

Category	Model	Used by
Mathematical and statistical methods	Mean reversion (MR)	[186], [174]
Classical machine learning methods	Convolutional neural network (CNN)	[69], [111]
	Dual-stage attention-based recurrent neural network (DARNN)	[186], [174]
	Feed-forward neural network (FNN)	[69], [214]
	Gated recurrent unit (GRU)	[149], [214]
	Long-short term memory network (LSTM)	[69], [176], [186], [111], [174], [72], [214]
	Support vector machine (SVM)	[111], [214]
GNN methods	Graph convolutional network (GCN)	[69], [149], [176], [111], [214]
	Financial Graph Attention Network (FinGAT) [66]	[149], [176]
	Hierarchical graph attention network (HATS) [89]	[176], [186], [174]

	Spatiotemporal hypergraph convolution network (STHGCN) [159]	[186], [174]

It is evident that there is no consensus regarding the most appropriate benchmark models, especially in the context of GNNs. The most common benchmark is the LSTM, which is considered an effective approach for processing long term information. The most commonly used GNN model is a vanilla graph convolutional network (GCN), followed by a more complex hierarchical graph attention network (HATS) proposed by Raehyun et al. in 2019 [89]. The HATS model has been proposed for predicting stock movements using relational data. It aggregates information from different types of relationships among data and incorporates this information into each stock representation. The source code for the HATS model is available at https://github.com/dmis-lab/hats.

5.3.5 Results

The accuracy of the proposed classification models is primarily evaluated in terms of accuracy, precision and F1 score. The only two papers with comparable results are Refs. [186] and [174], which study 758 frequently traded stocks collected from the A-share market in China from January 2013 to December 2019 (available at https://finance.sina.com.cn/stock). These two papers compare the results obtained by using 5, 10 and 20 trading days as records. For sake of simplicity, a comparison of the accuracy of the models in the two papers with 20 days only is provided in Tab. 12.

Table 12: Comparison of the average accuracy of the different models on the A-share market in China with 20 training days as records, expressed in terms of accuracy, precision, recall, and F1 score. The best results are underlined.

Model	Accuracy	Precision	Recall	F1 score
DARNN	38.41%	37.99%	39.24%	38.60%
GCN+LSTM	37.30%	39.28%	34.16%	36.54%
HATS	38.85%	38.70%	35.06%	36.78%
HGTAN	40.02%	41.77%	39.03%	40.32%
KG-GCN [186]	<u>51.38%</u>	<u>65.72%</u>	31.45%	39.27%
LSTM	35.03%	36.43%	34.23%	35.20%
MOM	35.73%	35.19%	32.82%	33.96%
MONEY [174]	39.90%	43.92%	<u>40.61%</u>	<u>42.20%</u>
MR	35.32%	38.03%	33.60%	35.68%
SFM	34.54%	26.93%	33.32%	29.49%
STHGCN	38.45%	37.22%	32.82%	34.87%
TGC	37.81%	36.96%	34.49%	35.67%

The two best models are the knowledge graph and graph convolution neural network (KG-GCN) [186] and the stock price movement prediction via convolutional network with adversarial hypergraph model (MONEY) [174], depending on the metrics considered.

5.4 Health

The fourth group of papers is "Health", which includes 8 out of 156 publications. These papers focus on critical aspects of health monitoring, disease modeling, and diagnostic tools, with particular emphasis on the spread and diagnosis of disease. All the papers working with functional magnetic resonance imaging (fMRI) data were excluded from the analysis, as the dataset was generated as image sequences rather than time series. This key difference in data structure makes them less relevant to the spatio-temporal focus of this review.

5.4.1 Overview

Applications of GNNs in the ”Health” group have been studied starting from 2021. The reason of this spread may be attributed to two key factors. The first reason is the growing presence of sensors in hospitals, which enable the collection of multivariate time series signals which can be used for the timely diagnosis of chronic diseases. The second reason is the spread of the COVID-19 pandemic, which has motivated researchers to investigate and forecast the spread of the virus. Epidemic forecasting is the most common topic among the selected papers. The prediction of epidemics presents two significant challenges. First, their seasonality can vary greatly over time, and they can manifest with different intensities and durations. Second, occasional pandemics can disrupt established patterns even for years. These complexities make the forecasting task more difficult, and machine learning and GNN models have been studied to address this issue. A common reference model for epidemic prediction is the SIR model [84], an acronym referring to individuals which stands for susceptible (S), infectious (I), and recovered (R). The SIR model divides the population into individuals who are susceptible to the disease, those who are infected and can spread it, and those who have recovered and are now immune, and uses differential equations to describe how the disease spreads. In general, some papers use it as benchmark (e.g., Ref. [220]).

All the selected papers are published in different journals, but primarily in the field of computer science. The majority of the corresponding authors are affiliated with academic institutions based in China.

5.4.2 Datasets

Tab. 13 provides a list of the public datasets utilized in the selected papers, along with links for accessing them.

Table 13: List of public datasets in the ”Health” group and their corresponding links.

Dataset	Used by	Link
Bonn dataset	[183]	http://dx.doi.org/10.1103/PhysRevE.64.061907 (source paper)
Brazilian COVID-19 data	[142]	https://github.com/lcaldeira/GrafoBrasilCovid
COVID-19 data	[220]	https://www.2019ncov.chinacdc.cn/
COVID-19 vaccinations	[118]	https://ourworldindata.org/us-states-vaccinations
eICU	[207]	https://doi.org/10.1038/sdata.2018.178 (source paper)
MIMIC-IV	[207]	https://physionet.org/content/mimiciv/2.0/
Nytimes COVID-19 data	[118]	https://github.com/nytimes/covid-19-data
Parkinson’s Progression Markers Initiative (PPMI)	[234]	http://www.ppmi-info.org/
Parkinson Speech data set (PS)	[234]	https://doi.org/10.1109/jbhi.2013.2245674 (source paper)
Spanish COVID-19 data	[137]	https://cnecovid.isciii.es/
Spikes and slow waves (SSW) dataset	[183]	http://dx.doi.org/10.1109/ICDM50108.2020.00067 (source paper)
US influenza	[227]	https://github.com/aI-area/DVGSN/tree/main/dataset

None of the papers in this section use the same dataset, so it is not possible to compare the results of the proposed models. Most of the datasets are related to the COVID-19 effects and have a daily granularity. In addition, some papers ([220], [142], [234], [207]) include exogenous variables that can be either context-related (e.g., geography, population, health conditions, vaccinations, economic factors), or specific to a single patient (including personal information such as age, gender, and medical conditions).

5.4.3 Proposed models

As for the taxonomy of the proposed models, 5 out of 8 papers use a convolutional GNN architecture. Two papers use a pure attentional model, while another paper presents a hybrid convolutional-attentional architecture. Different approaches are used to define the graph structure. Some papers base their graphs on the geographical distribution of the data (as in Refs. [220], [142] and [234]), and others use models that learn the graph structure directly, as in Refs. [227] and [118]. There is also a paper that uses a variant of the visibility algorithm [183]. In almost all the cases, the graph is static.

In terms of programming languages, this community uses only Python with PyTorch. As for loss functions, MSE is typically used for prediction tasks, and cross entropy is used for classification tasks. Tab. 14 shows the links to the related source codes.

Table 14: List of source codes of the "Health" models in the review.

Model	Link
Dynamic virtual graph significance networks (DVGSN) [227]	https://github.com/aI-area/DVGSN
Deep learning of contagion dynamics on complex networks [137]	https://doi.org/10.5281/zenodo.4974521
Sparse spectra graph convolutional network (SSGCNet) [183]	https://github.com/anonymous2020-source-code/WNFG-SSGCNet-ADMM
Spatial-Temporal Graph Convolutional Network (STGCN) [142]	https://github.com/lcaldeira/CovidPandemicForecasting
Time-aware Context-Gated Graph Attention Network (T-ContextGGAN) [207]	https://github.com/OwlCitizen/TContext-GGAN

5.4.4 Benchmark models

Tab. 15 lists the benchmark models in the "Health" group that are discussed in at least two papers.

Table 15: List of benchmark models in the "Health" group divided per category.

Category	Model	Used by
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	[227], [220], [142]
Classical machine learning methods	Feed-forward neural network (FNN)	[183], [227]
	Long-short term memory network (LSTM)	[220], [118]

There are no particularly relevant benchmark models, and none fall within the category of GNNs. This is because GNNs have not been widely studied in the context of health.

5.4.5 Results

In each paper, the authors claim that the proposed GNN-based model outperforms the benchmarks. The most common error metrics are the MAE and the MSE for forecasting problems and accuracy, sensitivity and specificity for classification problems. A comparison of the accuracy of the different models is not possible due to the lack of common benchmark datasets.

5.5 Mobility

The topic that includes the largest number of papers identified by the query (39 out of 156) is "Mobility", which regards the movement of people. It includes urban traffic, air travel, and bicycle demand, among other applications. Given the large number of articles in this group, a more detailed comparison of benchmarks, models, and results can be provided.

5.5.1 Overview

Early traffic prediction is essential for improving the efficiency of transportation systems, helping drivers plan their trips more effectively, and preventing urban congestion. The advent of smart cities infrastructures and transportation systems has contributed to the collection of rich data from road sensors that can be used for this purpose. However, making accurate traffic forecasts is challenging due to constantly changing traffic patterns over time and space, as well as the influence of external factors such as weather conditions and special events. Unlike classical statistical and machine learning models, GNNs can be particularly effective for traffic forecasting due to their ability to model complex relationships in spatial and temporal domain. The increasing number of papers published each year in this group reflects both the growing research interest in this field and the growing confidence in GNN models. The most commonly investigated areas regard urban traffic ([133], [185], [33], [108], [107], [103], [128], [205], [127], [79], [106], [95], [94], [210], [59], [54], [231], [85], [146], [134], [241], [20], [2], [13], [55], [36], [15], [77]), especially urban traffic flow and urban traffic speed. Among the journals where the selected papers were published, *Applied Intelligence* by Springer is the most common, with 5 out of 39 papers. This is followed by *ACM Transactions on Intelligent Systems and Technology* and *ACM Transactions on Knowledge Discovery from Data*, both published by the Association for Computing Machinery, each with 4 out of 39 papers. Most of the corresponding authors are affiliated with Chinese institutions.

5.5.2 Datasets

Tab. 16 provides a list of the public datasets mentioned in the selected papers, along with the links to access them.

Table 16: List of public datasets in the "Mobility" group and their corresponding links.

Dataset	Used by	Link
CAAC flights	[14]	http://www.caac.gov.cn/index.html
CD-HW	[20]	https://doi.org/10.1109/ACCESS.2020.3027375 (source paper)
City Bike NYC	[203], [122]	https://citibikenyc.com/system-data
DiDi Beijing	[193]	https://github.com/didi/TrafficIndex
DiDi Chengdu	[133], [108]	https://gaia.didichuxing.com/
Huai'an Bus Transaction	[65]	https://www.pandabus.cn/panda/panda-minibus.html
Los-loop	[128]	https://github.com/lehaifeng/T-GCN/tree/master/data
METR-LA	[133], [107], [103], [106], [95], [94], [59], [231], [85], [20], [13]	https://paperswithcode.com/dataset/metr-la
Milan network	[146]	https://github.com/arunasubbiah/milan-telecom-data-modeling
NE-BJ	[103]	https://github.com/tsinghua-fib-lab/Traffic-Benchmark
NYC-Taxi	[102]	https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

PeMS03	[79], [94], [210], [54], [241], [55]	https://www.kaggle.com/datasets/elmahy/pems-dataset
PeMS04 (PeMSD4)	[185], [33], [107], [230], [79], [94], [210], [54], [85], [241], [2], [55], [36], [15]	https://paperswithcode.com/dataset/pems04
PeMS07 (PeMSD7)	[79], [95], [94], [54], [241], [2], [55]	https://paperswithcode.com/dataset/pems07
PeMS08 (PeMSD8)	[185], [33], [107], [79], [210], [54], [85], [241], [55], [36], [15]	https://paperswithcode.com/dataset/pems08
PEMS-BAY	[103], [106], [95], [59], [231], [85]	https://paperswithcode.com/dataset/pems-bay
Q-Traffic	[134]	https://github.com/JingqingZ/BaiduTraffic#Dataset
RCOTP	[185]	https://developer.ibm.com/exchanges/data/all/airline/
UVDS	[13]	https://doi.org/10.1007/978-3-030-73280-6_6 (source paper)
TaxiBJ	[20]	https://www.microsoft.com/en-us/research/publication/forecasting-citywide-crowd-flows-based-big-data/
Taxi Shenzhen	[128], [77]	https://github.com/lehaifeng/T-GCN/tree/master/data
TLC Taxi	[124]	https://www.nyc.gov/site/tlc/about/tlc-trip-record-data.page

The most popular datasets are PeMS ones (http://pems.dot.ca.gov/), provided by the California Transportation Agency Performance Measurement System, which include various versions differing in time range, spatial coverage, and the number of sensors, and METR-LA, collected from loop detectors in Los Angeles County highway. The number of sensors is in the hundreds, and so is the number of nodes in the graph. For a more detailed overview of the benchmark datasets in the traffic domain, see Ref. [75]. Other common public traffic datasets can be found at https://paperswithcode.com/task/traffic-prediction. In terms of external data, the most commonly used are weather conditions, time information (time of day and day of week) and events (e.g., holidays), as well as information about the road network (e.g., points of interest).

The majority of the papers utilize data with a 5-minute granularity, and provide forecasts for horizons ranging from 5 minutes to 1 hour ahead. In addition to imputation of missing values, in almost half of the cases the pre-processing of the data includes data normalization (min-max or Z-score normalization) and the selection of time windows regarding recent, daily and weekly data (as in 8 out of 39 papers).

5.5.3 Proposed models

As for the proposed models, 18 out of 39 belong to the pure convolutional GNN paradigm, followed by 11 attentional GNNs, 9 hybrid convolutional-attention architectures, and 1 recurrent GNN. Regarding the definition of the graph structure, most of the papers discuss it in detail. Half of the papers are based on a pre-defined adjacency matrix, and among the remaining papers that propose models that learn the adjacency matrix on their own, a further half is based on a pre-initialization of the matrix, as for example in Ref. [79]. Here, more than in any other group, there are multiple ways to define the adjacency matrix, taking into account either the structure of the road network, the actual flow of people, or a combination of different information. More in detail, some models use the road connectivity ([230], [231], [146], [77]), others their spatial distance ([133], [102], [107], [95], [13], [15]), and some others incorporate extra information about the so-called points of interest (such as Refs. [203], [102]). Other models instead consider some similarity measures between the time series ([33], [54], [85], [146]), such as the correlation coefficient or cosine similarity. Still others directly use the number of people traveling on the road at a given time step ([203], [193], [14], [38]).

The two most common loss functions used to train the models are the MSE and the MAE. Few papers consider a combination of loss functions, especially when dealing with a model that has to learn the graph structure by itself (Refs. [185], [20], [55]). Not all papers specify the language or library used for the code. Among those that do, Python is the most common language, with the majority using PyTorch, while only a few researchers use TensorFlow. In addition, a few papers provide a link to the source code for the proposed model. The papers that provide such links are listed in Tab. 17.

Table 17: List of source codes of the "Mobility" models in the review.

Model	Link
3-Dimensional Graph Convolution Network (3DGCN) [203]	https://github.com/FIBLAB/3D-DGCN
Adaptive generalized PageRank graph neural network (AGP-GNN) [59]	https://github.com/guoxiaoyuatbjtu/agp-gnn
Automated dilated spatio-temporal synchronous graph network (Auto-DSTSGN) [79]	https://github.com/jinguangyi-uto-DSTSGN
Dynamic multi-view graph neural network for city-wide traffic inference (CTVI+) [33]	https://github.com/dsj96/TKDD
Dynamic Graph Convolutional Recurrent Network (DGCRN) [103]	https://github.com/tsinghua-fib-lab/Traffic-Benchmark
Spatio-temporal Causal Graph Attention Network (STCGAT) [241]	https://github.com/zsqZZU/STCGAT/tree/v1.0.0
Spatial-Temporal Graph Convolutional Neural Network with LSTM layers (STGCN-LSTM) [2]	https://github.com/ant-agafonov/stgcn-lstm
Spatio-Temporal Graph Mixformer (STGM) [95]	https://github.com/mouradost/stgm

5.5.4 Benchmark models

Tab. 18 lists the benchmark models used in the papers in the "Mobility" group. The benchmarks are categorized into mathematical and statistical methods, classical machine learning models, and GNN models, and only those appearing in more than two papers are included.

Table 18: List of benchmark models in the "Mobility" group divided per category.

Category	Model	Used by
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	[133], [203], [185], [102], [108], [103], [65], [128], [127], [184], [106], [59], [146], [20], [14], [15], [77]
	Historical average (HA)	[133], [203], [102], [108], [103], [65], [193], [128], [106], [95], [231], [146], [241], [36], [15], [77]
	Vector autoregression (VAR)	[107], [103], [20], [36], [15]
Classical machine learning methods	Feed-forward neural network (FNN)	[133], [33], [103], [205], [122], [231], [238], [134], [20]
	Gated recurrent unit (GRU)	[108], [107], [65], [127], [238], [146], [134], [2], [36], [15], [77]

	Long-short term memory network (LSTM)	[133], [102], [108], [107], [103], [127], [184], [79], [106], [94], [210], [59], [231], [238], [85], [241], [20], [2], [55], [36], [15]
	Long-short term time series network (LST-Net) [97]	[193], [95]
	Seq2Seq [175]	[205], [134]
	Spatial and temporal normalization for multivariate time series forecasting (ST-Norm) [35]	[59], [54]
	Support vector regression (SVR)	[107], [103], [128], [184], [106], [124], [146], [14], [55], [77]
	Extreme gradient boosting (XGBoost) [23]	[33], [122]
GNN methods	Adaptive graph convolutional recurrent network (AGCRN) [4]	[185], [108], [103], [65], [95], [54], [134], [241], [55], [36]
	Attention-based spatial-temporal graph convolutional network (ASTGCN) [57]	[133], [185], [108], [107], [103], [184], [79], [95], [94], [210], [54], [238], [241], [20], [2], [55], [36], [15]
	Dual-stage attention-based recurrent neural network (DA-RNN) [156]	[102], [205]
	Diffusion convolutional recurrent neural network (DCRNN) [119]	[133], [203], [185], [102], [103], [65], [128], [184], [79], [106], [95], [94], [210], [59], [54], [231], [85], [134], [241], [20], [13], [14], [55], [36], [15]
	Dynamic spatial-temporal aware graph neural network (DSTAGNN) [98]	[185], [241]
	GeoMAN [123]	[102], [15]
	Graph convolutional network (GCN)	[230], [77]
	Graph multi-attention network (GMAN) [242]	[103], [106], [95], [59], [85], [13]
	Graph WaveNet (GWN) [202]	[133], [185], [103], [65], [79], [106], [95], [94], [210], [59], [54], [85], [134], [13]
	Multi-range attentive bicomponent graph convolutional network (MRA-BGCN) [24]	[106], [59]
	Multivariate time series forecasting with graph neural network (MTGNN) [201]	[103], [106], [95], [94], [59], [54], [85], [134], [13]
	Multi-view graph convolutional network (MVGCN) [172]	[203], [102]
	Spatial-temporal fusion graph neural network (STFGNN) [114]	[108], [65], [79], [210], [54], [241], [55]
	Spatio-temporal graph convolutional network (STGCN) [216]	[133], [203], [185], [102], [107], [103], [65], [127], [184], [79], [106], [95], [94], [210], [59], [54], [231], [238], [85], [134], [20], [2], [13], [14], [55], [36], [15]
	Spatial temporal graph neural network (STGNN) [188]	[203], [128]
	Spatial-temporal graph ODE networks (STGODE) [43]	[107], [79], [54], [241]

Deep-meta-learning based model (ST-MetaNet) [148]	[102], [103], [106], [59]
Spatio-temporal synchronous graph convolutional network (STSGCN) [169]	[108], [107], [103], [79], [210], [54], [241], [55], [36]
Temporal graph convolutional network (T-GCN) [239]	[128], [184], [94], [238], [146]

As for the basic mathematical and statistical methods, two widely used benchmarks are the ARIMA model and historical average model (HA), which uses the average of past observations as the forecast for future values. Despite their apparent simplicity, these models are sometimes shown to be very powerful benchmarks, with an accuracy comparable to that of more complex models. As for the traditional machine learning models, LSTMs are widely recognized as a type of recurrent neural network capable of handling and long-term dependencies in traffic data. As for GNN-based models instead, the three most used models are, in order, the spatio-temporal graph convolutional network (STGCN) [216], the diffusion convolutional recurrent neural network (DCRNN) [119], and the attention-based spatial-temporal graph convolutional network (ASTGCN) [57], all developed specifically for the traffic forecasting problem.

The STGCN model was proposed by Yu et al. in 2018, and it integrates graph convolution and gated temporal convolution through spatio-temporal convolutional blocks. The source code is available at https://github.com/VeritasYin/STGCN_IJCAI-18. The DCRNN model was proposed by Li et al. in 2017, and it aims to capture the spatial dependency using bidirectional random walks on the graph, and the temporal dependency using the encoder-decoder architecture with scheduled sampling. The code can be accessed at https://github.com/liyaguang/DCRNN. Finally, the ASTGCN model was proposed by Guo et al. in 2019, and it models in parallel recent, daily-periodic and weekly-periodic dependencies as three independent components with a spatio-temporal attention mechanism to capture the dynamic spatio-temporal correlations, and a spatio-temporal convolution which simultaneously employs graph convolutions to capture the spatial patterns. The code is available at https://github.com/Davidham3 /ASTGCN-2019-mxnet. For a more comprehensive list of source codes for the most dated benchmark GNN models in the traffic domain see Ref. [76].

5.5.5 Results

In all papers, the authors claim that the proposed GNN-based models are able to outperform the other benchmarks. However, there are a limited number of situations in which some simple statistical and mathematical models demonstrate comparable accuracy, as it can be observed in Tabs. 19 and 20.

For the and comparison and evaluation of the models, the most commonly used error metrics are MAE, RMSE, and MAPE. Few papers also use different metrics, such as the coefficient of determination R^2. However, despite the use of the same metrics and the availability of widely used datasets, comparing models is not trivial because different papers often focus on different time windows of a dataset.

In Tab. 19 it is shown the accuracy of the different models on the METR-LA dataset with a 5-minute granularity from 1$^{\text{st}}$ March 2012 to 30$^{\text{th}}$ June 2012 for 15, 30 and 60 minute time horizons, expressed in terms of MAE, MAPE and RMSE.

Table 19: Comparison of the average accuracy of the different models on the METR-LA dataset for 15, 30 and 60 minute time horizons, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with $\star$ are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the papers.

Time horizon	15 min			30 min			60 min		
Metrics	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE
AGCRN	2.87	7.70	5.58	3.23	9.00	6.58	3.62	10.38	7.51
AGP-GNN [59]	2.71	7.21	5.25	3.04	8.15	6.20	3.41	9.70	7.20
ARIMA	3.99	9.60	8.12	5.15	12.70	10.45	6.90	17.40	13.23

ASTGCN	4.86	9.21	9.27	5.43	10.13	10.61	6.51	11.64	12.52
DCRNN	2.77	7.30	5.38	3.15	8.80	6.45	3.60	10.50	7.60
DGCRN [103]	2.62	6.63	5.01	2.99	8.02	6.05	3.44	9.73	7.19
DST-GCNN [20]	2.68	7.20	5.35	3.01	8.50	6.23	3.41	10.30	7.47
DyGCN-LSTM [94]	2.64	6.35	4.64	3.24	8.04	5.24	3.53	9.30	6.53
FC-GAGA	2.75	7.25	5.34	3.10	8.57	6.30	3.51	10.14	7.31
FNN	3.99	9.90	7.94	4.23	12.90	8.17	4.49	14.00	8.69
GA-LSTM [231]	2.30	7.01	4.97	2.98	8.50	6.00	3.55	9.97	7.23
GGRU	2.71	6.99	5.24	3.12	8.56	6.36	3.64	10.62	7.65
GMAN	2.77	7.25	5.48	3.07	8.35	6.34	3.40	9.72	7.22
GWN	2.69	6.90	5.15	3.07	8.37	6.22	3.53	10.01	7.37
HA	4.16	13.00	7.80	4.16	13.00	7.80	4.16	13.00	7.80
LSTM	3.44	9.60	6.30	3.77	10.90	7.23	4.37	13.20	8.69
MCFGNN* [27]	2.31	5.86	5.29	2.66	6.89	6.27	3.05	7.65	7.20
MRA-BGCN	2.67	6.80	5.12	3.06	8.30	6.17	3.49	10.00	7.30
MS-GAT	2.65	6.43	2.99	4.83	8.31	5.91	6.48	9.48	8.11
MTGNN	2.69	6.86	5.18	3.05	8.19	6.17	3.49	9.87	7.23
MTGODE* [82]	2.66	6.87	5.10	3.00	8.19	6.05	3.39	9.80	7.05
MVST-GNN [106]	2.70	5.19	6.97	3.06	8.12	6.08	3.40	9.60	6.98
SDGCN	2.76	7.16	5.38	3.15	8.53	6.46	3.61	9.87	7.43
STAG-GCN [133]	2.67	7.00	5.23	3.07	8.26	6.15	3.50	9.93	7.24
STFGNN*	2.57	6.51	4.73	2.83	7.46	5.46	3.18	8.81	6.40
STGCN	2.88	7.62	5.74	3.47	9.57	7.24	4.59	12.70	9.40
STGODE*	3.47	8.76	6.76	4.36	11.14	8.47	5.50	14.32	10.33
STG-NCDE*	3.77	8.54	9.47	4.84	10.63	12.04	6.35	13.49	14.94
STGRAT	2.60	6.61	5.07	3.01	8.15	6.21	3.49	10.01	7.42
ST-MetaNet	2.69	6.91	5.17	3.10	8.57	6.28	3.59	10.63	7.52
STSGCN	3.31	8.06	7.62	4.13	10.29	9.77	5.06	12.91	11.66
SVR	3.99	9.30	8.45	5.05	12.10	10.87	6.72	16.70	13.76
TF-GAN [85]	2.63	6.55	4.94	3.06	8.36	6.20	3.32	9.48	7.11
T-GCN	3.03	7.81	5.26	3.52	9.45	6.12	4.30	11.80	7.31
VAR	4.42	10.20	7.89	5.41	12.70	9.13	6.52	15.80	10.11
WaveNet	2.99	8.04	5.89	3.59	10.25	7.28	4.45	13.62	8.93

The results on the METR-LA dataset are not uniform, and the best performing models vary depending on the metric and the time horizon. However, especially for longer time horizons, the Dynamic Graph Convolution LSTM Network (DyGCN-LSTM) [94] appears to be the most accurate one (excluding the "Generic"* models, among which the best model is the multichannel fusion graph neural network (MCFGNN) [27]).

Tab. 20 displays the accuracy of various models on the PEMS-BAY dataset with a 5-minute granularity and data spanning from 1st January 2017 to 30th June 2017 for 15, 30 and 60 minute time horizons, with results expressed in terms of MAE, MAPE and RMSE.

Table 20: Comparison of the average accuracy of the different models on the PEMS-BAY dataset for 15, 30 and 60 minute time horizons, expressed in terms of MAE, MAPE and RMSE. The smallest errors are underlined. Numbers from the papers.

Time horizon	15 min			30 min			60 min		
Metrics	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE

AGCRN	1.37	2.94	2.87	1.69	3.87	3.85	1.96	4.64	4.54
AGP-GNN [59]	1.33	2.79	2.86	1.61	3.66	3.67	1.86	4.30	4.34
ARIMA	1.62	3.50	3.30	2.33	5.40	4.76	3.38	8.30	6.50
ASTGCN	1.52	3.22	3.13	2.01	4.48	4.27	2.61	6.00	5.42
DCRNN	1.38	2.90	2.95	1.74	3.9	3.97	2.07	4.90	4.74
DGCRN [103]	1.28	2.66	2.69	1.59	3.55	3.63	1.89	4.43	4.42
FC-GAGA	1.36	2.87	2.86	1.68	3.80	3.80	1.97	4.67	4.52
FNN	2.20	5.19	4.42	2.30	5.43	4.63	2.46	5.89	4.98
GMAN	1.34	2.81	2.82	1.62	3.62	3.72	1.86	4.31	4.32
GWN	1.30	2.73	2.74	1.63	3.67	3.70	1.95	4.63	4.52
HA	2.88	6.80	5.59	2.88	6.80	5.59	2.88	6.80	5.59
LSTM	2.05	4.80	4.19	2.20	5.20	4.55	2.37	5.70	4.96
MRA-BGCN	1.29	2.90	2.72	1.61	3.80	3.67	1.91	4.60	4.46
MTGNN	1.32	2.77	2.79	1.65	3.69	3.74	1.94	4.53	4.49
MTGODE⋆ [82]	1.29	2.72	2.73	1.61	3.61	3.66	1.88	4.39	4.31
MVST-GNN [106]	1.30	2.73	2.74	1.57	3.56	3.54	1.80	4.19	4.26
SDGCN	1.35	2.89	2.88	1.69	3.87	3.91	1.99	4.69	4.59
STGCN	1.36	2.90	2.96	1.81	4.17	4.27	2.49	5.79	5.69
STGODE⋆	1.43	2.99	2.88	1.84	3.84	3.90	2.30	4.61	4.89
STG-NCDE⋆	1.38	2.91	2.93	1.71	3.91	3.84	2.03	4.82	4.58
STGRAT	1.29	2.67	2.71	1.61	3.63	3.69	1.95	4.64	4.54
STID	1.30	2.73	2.81	1.62	3.68	3.72	1.89	4.47	4.4
ST-MetaNet	1.36	2.82	2.90	1.76	4.00	4.02	2.20	5.45	5.06
ST-Norm	1.34	2.82	2.88	1.67	3.75	3.83	1.96	4.62	4.52
STSGCN	1.44	3.04	3.01	1.83	4.17	4.18	2.26	5.40	5.21
SVR	1.85	3.80	3.59	2.48	5.50	5.18	3.28	8.00	7.08
VAR	1.74	3.60	3.16	2.32	5.00	4.25	2.93	6.50	5.44
WaveNet	1.39	2.91	3.01	1.83	4.16	4.21	2.35	5.87	5.43

The results on the the PEMS-BAY dataset indicate that the dynamic graph convolutional recurrent network (DGCRN) [103] is the most accurate model for the 15-minute forecasting horizon, while the multi-view spatial-temporal graph neural network (MVST-GNN) [106] is the best model for the longer horizons.

As for the other PeMS datasets (PeMS03, PeMS04, PeMS07 and PeMS08), the results are largely consistent with an indication that the automated dilated spatio-temporal synchronous graph network (Auto-DSTSGN) [79] is the most accurate model (excluding the "Generic"⋆ models), as shown in Tabs. 21, 22, 23, and 24. Tab. 21 reports the accuracy of the different models applied to the PeMS03 dataset, which includes data from 1st September 2018 to 30th November 2018 at a 5-minute granularity for a 60-minute time horizon, with results given in terms of MAE, MAPE and RMSE.

Table 21: Comparison of the average accuracy of the different models on the PeMS03 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with ⋆ are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the papers.

Time horizon	60 min		
Metrics	MAE	MAPE	RMSE
AGCRN	17.69	19.40	29.66
ASTGCN	17.69	19.40	29.66

Auto-DSTSGN [79]	<u>14.59</u>	<u>14.22</u>	<u>25.17</u>
AutoSTG	16.27	16.10	27.63
DCGCN [54]	15.29	-	25.98
DCRNN	18.18	18.91	30.31
Graph WaveNet	19.85	19.31	32.94
LSGCN	17.94	-	29.85
LSTM	21.33	23.33	35.11
STAGCN [55]	15.40	14.48	26.23
STCGNN [210]	15.81	14.59	27.23
STFGCN	16.77	16.30	28.34
STGCN	17.49	17.15	30.12
STGODE	16.53	16.68	27.79
STSGCN	17.48	16.78	29.21
SVR	21.97	21.51	35.29

In Tab. 22 is shown the accuracy of the different models on the PeMS04 dataset with a 5-minute granularity and data from 1$^{\text{st}}$ January 2018 to 28$^{\text{th}}$ February 2018 a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE.

Table 22: Comparison of the average accuracy of the different models on the PeMS04 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with $\star$ are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the papers.

Time horizon		60 min	
Metrics	MAE	MAPE	RMSE
AGCRN	19.83	12.97	32.26
ARIMA*	33.73	24.18	48.80
ASTGCN	22.93	16.56	35.22
Auto-DSTSGN [79]	18.85	13.21	30.48
Autoformer*	23.76	18.01	36.59
AutoSTG	20.38	14.12	32.51
Crossformer*	20.40	14.62	32.79
DCGCN [54]	20.28	-	31.65
DCRNN*	19.71	13.54	31.43
DGCRN*	19.04	12.80	30.82
DMGF-Net [107]	20.59	13.63	32.43
DSA-NET*	22.79	16.03	35.77
DSTGN* [120]	18.61	12.31	30.79
DSTIGNN* [48]	<u>18.41</u>	12.45	29.97
FEDFormer*	22.86	16.04	35.07
GMAN*	20.93	14.06	33.34
GODERN-FS* [225]	19.17	12.74	30.96
GRU	23.68	16.44	39.27
GWN*	19.36	13.31	31.72
HA*	38.03	27.88	59.24
LSGCN	21.53	13.18	33.86
LSTM*	23.81	18.12	36.62

MTGNN⋆	24.89	17.29	39.66
MTGODE⋆	19.55	13.08	32.99
SCINet⋆	19.29	<u>11.89</u>	31.28
SDGL⋆ [121]	18.65	12.38	31.30
STAGCN [55]	19.02	12.46	30.75
STCGNN [210]	19.39	12.71	31.17
STFGCN	19.83	13.02	31.88
STG2SEQ	25.20	18.77	38.48
STGODE⋆	20.84	13.77	32.82
STIDGCN⋆	18.47	12.42	<u>29.90</u>
STGCN⋆	21.16	13.83	34.89
STSGCN⋆	21.08	13.88	33.83
STGODE	20.84	13.76	32.84
STSGCN	21.19	13.90	33.65
SVR	28.70	19.20	44.56
TCN⋆	23.22	15.59	37.26
VAR⋆	23.51	17.85	36.39

The MAE, MAPE and RMSE of the different models on the PeMS07 dataset, with data from 1st May 2017 to 31st August 2017, a 5-minute granularity and a 60-minute time horizon, are presented in Tab. 23.

Table 23: Comparison of the average accuracy of the different models on the PeMS07 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The smallest errors are underlined. Numbers from the papers.

Time horizon	60 min		
Metrics	MAE	MAPE	RMSE
AGCRN	22.37	9.12	36.55
ASTGCN	28.05	13.92	42.57
Auto-DSTSGN [79]	<u>20.08</u>	<u>8.57</u>	<u>33.02</u>
AutoSTG	23.22	9.95	36.47
DCGCN [54]	22.06	-	34.66
DCRNN	25.30	11.66	38.58
GWN	26.85	12.12	42.78
LSGCN	27.31	-	41.46
LSTM	29.98	13.20	45.94
STAGCN [55]	21.10	8.92	34.10
STFGCN	22.07	9.21	35.80
STGCN	25.38	11.08	38.78
STGODE	22.59	-	37.54
STSGCN	24.26	10.21	39.03
SVR	32.49	14.26	50.22

Finally, Tab. 24 displays the accuracy of the various models on the PeMS08 dataset with a 5-minute granularity and data spanning from 1st July 2016 to 31st August 2016 for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE.

Table 24: Comparison of the average accuracy of the different models on the PeMS08 dataset for a 60-minute time horizon, expressed in terms of MAE, MAPE and RMSE. The results of the models marked with ⋆ are taken from papers in the "Generic" group. The smallest errors are underlined. Numbers from the papers.

Time horizon		60 min	
Metrics	MAE	MAPE	RMSE
AGCRN	15.95	10.09	25.22
ARIMA⋆	31.09	22.73	44.32
ASTGCN	18.61	13.08	28.16
Auto-DSTSGN [79]	14.74	9.45	23.76
Autoformer⋆	21.04	15.98	31.33
AutoSTG	16.37	10.36	25.46
Crossformer⋆	16.25	11.14	26.14
DCGCN [54]	15.68	-	24.39
DCRNN⋆	15.26	9.96	24.28
DMGF-Net [107]	16.48	10.56	25.73
DSA-NET⋆	17.14	11.32	26.96
DSTIGNN⋆ [48]	<u>13.88</u>	<u>9.04</u>	<u>23.64</u>
FEDformer⋆	19.55	13.58	29.30
GMAN⋆	16.97	11.32	26.70
GODERN-FS⋆ [225]	15.59	9.95	24.79
GRU	22.00	13.33	36.24
GWN⋆	15.07	9.51	23.85
HA⋆	34.86	24.07	52.04
LSGCN	17.73	11.20	26.76
LSTM	22.20	14.20	34.06
MTGNN⋆	18.28	12.15	30.05
MTGODE⋆	15.61	10.15	25.96
SCINet⋆	15.78	9.97	24.60
SDGL⋆ [121]	14.93	9.61	24.13
STAGCN [55]	15.36	9.80	24.32
STCGNN [210]	15.55	10.02	24.61
STFGCN	16.64	10.60	26.22
STIDGCN⋆	14.10	9.15	23.72
STG2SEQ	20.17	17.32	30.71
STGCN⋆	17.50	11.29	27.09
STGODE	16.79	10.58	26.01
STSGCN	17.13	10.96	26.80
SVR	23.25	14.64	36.16
TCN⋆	22.72	14.03	35.79
VAR⋆	22.07	14.04	31.02

5.6 Predictive monitoring

In modern industry, sensor-based monitoring of processes has become essential. This pairs with the rapid growth of the Internet of Things (IoT), which aims at a smarter management across various applications [109]. In this framework, multi-sensor systems can be used to detect anomalies in complex scenarios and to monitor the overall status of a system. Predictive monitoring is a task that involves the continuous observation and analysis of a system, in order to forecast its future states and verify whether the predicted outcomes meet certain standards. This predictive monitoring task is important because it significantly improves efficiency, reliability, and cost of industrial operations. Related approaches include several techniques, such as anomaly detection, fault diagnosis and remaining useful life estimation.

Despite the specificity of the field, 16 out of 156 papers address the topic of predictive monitoring. This includes anomaly detection ([109], [112]), fault diagnosis ([177], [221], [100], [226], [141], [233], [99]) and RUL estimation ([192], [25], [182], [138], [212], [93], [196]). The use of GNNs in these analyses is justified by the necessity of using a model capable of capturing the spatio-temporal correlations among the many sensors present in the system.

5.6.1 Overview

Predictive monitoring includes several techniques, such as anomaly detection, fault diagnosis and remaining useful life estimation. Anomaly detection is a technique that aims to identify abnormal data that are not due to random deviations, and are rather generated by a different underlying mechanism [62]. It is a prerequisite part of fault diagnosis [78]. Fault diagnosis is the process of determining whether a fault has occurred in a system, including the identification of the time, location, type, and severity of the fault. It is usually considered to be a classification problem. As for remaining useful life (RUL) estimation, it aims to determine how long a machine will operate before it needs to be repaired or replaced, and it is useful for scheduling maintenance interventions.

The selected papers implement these three techniques, with anomaly detection being less prevalent than the other two. The main applications studied are industrial (e.g., bearings fault diagnosis [221], [100], [141], [138], [212]) and mechanical (e.g, engines RUL estimation [192], [25], [182], [93]). There are also two papers dealing with energy related tasks, specifically fault diagnosis of photovoltaic systems [177] and energy networks [226]. They are included in this section due to their specific focus on fault classification rather than on energy-related time series forecasting. It shoud also be underlined that the majority of the papers aim at solving a classification task, which is typical of anomaly detection and fault diagnosis. As for RUL estimation, the quantity to be predicted is the RUL itself. For this reason, we do not refer to forecasting time horizons as in the other sections, since the goal is to estimate the RUL rather than to forecast data over future time intervals.

The majority of the collected papers were published in 2023 by authors affiliated with Chinese universities. The most popular journal for these topics is *IEEE Transactions on Instrumentation and Measurement by the Institute of Electrical and Electronics Engineers* by IEEE, with 5 out of 15 papers. All other journals contain only one of the selected articles. It can be observed that the majority of the articles are published in IEEE journals.

5.6.2 Datasets

Tab. 25 contains a list of the public datasets used in the selected papers, with the links to access them.

Table 25: List of public datasets in the "Predictive monitoring" group and their corresponding links.

Dataset	Used by	Link
Air Quality China	[109]	https://www.aqistudy.cn/historydata/
Air Quality - TPS	[109]	https://www.kaggle.com/amritpal333/tps-july-2021-original-dataset-clean
C-MAPSS	[192], [25], [182], [93]	https://ntrs.nasa.gov/api/citations/20070034949/downloads/20070034949.pdf
CWRU bearing dataset	[100], [99]	http://csegroups.case.edu/bearingdatacenter/home
JNU bearing dataset	[100]	http://mad-net.org:8765/explore.html?id=9&t=0.9355271549540183
NASA battery dataset	[196]	http://ti.arc.nasa.gov/project/prognostic-data-repository

NASA prognostics data	[233]	https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/#bearing
N-CMAPSS	[192], [182]	https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/
MFPT	[99]	https://api.semanticscholar.org/CorpusID:26870683 (source paper)
NREL PV	[177]	https://www.nrel.gov/
PRONOSTIA	[138], [212]	https://hal.science/hal-00719503/document (source paper)
SEU bearing dataset	[100]	https://github.com/cathysiyu/Mechanical-datasets
XJTUGearbox and XJTUSpurgear	[99]	http://dx.doi.org/10.1016/j.ymssp.2021.108653 (source paper)

The two most popular datasets are C-MAPSS and N-CMAPSS, two well-known datasets for RUL prediction provided by NASA. C-MAPSS describes the deterioration of aircraft engines by recording temperature, pressure, and fan speed during the cruise phase (https://ntrs.nasa.gov/api/citations/20070034949/downloads/20070034949.pdf). N-CMAPSS is an extended version of C-MAPSS, whose records cover climbing, cruising, and descending flight conditions (https://ti.arc.nasa.gov/tech/dash/groups/pcoe/prognostic-data-repository/). Practically no papers use exogenous variables, with the exception of Ref. [177], which evaluates the impact of meteorological variables on fault diagnosis of photovoltaic systems.

The granularity of the studied time series is highly variable, ranging from 1 hour to fractions of seconds. Many papers report the frequency of the sensors, with values ranging from 1 Hz to 50 kHz. Most datasets are normalized, by either using min-max normalization or Z-score normalization. In some papers, a data augmentation procedure is employed to mitigate the natural imbalance between the number of normal and anomalous conditions.

5.6.3 Proposed models

Half of the proposed GNN models (9 out of 16 papers) fall under the category of pure convolutional models, followed by 4 attentional GNNs, 2 hybrid models, and one whose description does not clarify which class of the taxonomy it belongs to (Ref. [138]). Almost all the models have a graph learning module, so that the graph structure is rarely defined a priori by the researchers. Three papers ([100], [141], [182]) use the visibility graph algorithm proposed by Lacasa et al. in Ref. [96] for converting the time series into a graph.

The most common loss functions in this group are the cross entropy function for classification problems, and MSE or RMSE for RUL forecasting problems. Most of the papers mention the Python language and the PyTorch library, but only two papers provide a link to the source code of their model, and in both cases, it is for RUL prediction. The source code for the convolution-graph attention network (ConvGAT) [25] is available at https://github.com/CUG-FDGroup, while the one for the graph network with causal connectivity and temporal convolutional neural network feature extractor proposed in Ref. [138] is available at https://github.com/mylonasc/gnn-tcnn.

5.6.4 Benchmark models

Tab. 26 presents the benchmark models employed in the ”Predictive monitoring” group by at least two articles examined in this review.

Table 26: List of benchmark models in the ”Predictive monitoring” group divided per category.

Category	Model	Used by
Classical machine learning methods	Attention-based long-short term memory network	[25], [93]

	Feature-attention based bidirectional GRU and CNN model (AGCNN) [246]	[25], [182], [93]
	Bidirectional long-short term memory network (BiLSTM) [52]	[192], [25], [182], [93]
	Convolutional neural network (CNN)	[109], [226], [192], [25], [182], [212], [93]
	Decision tree (DT)	[109], [226]
	Feed-forward neural network (FNN)	[100], [138]
	Gradient boosting (GB)	[226], [182]
	Gated recurrent unit (GRU)	[177], [226], [212]
	Logistic regression (LR)	[109], [226]
	Long-short term memory network (LSTM)	[100], [226], [182], [93], [196]
	Random forest (RF)	[226], [182]
	Support vector machine (SVM)	[109], [226]
	Transformer [178]	[192], [182]
GNN methods	Graph attention network (GAT) [179]	[221], [226], [99]
	Graph convolutional network (GCN)	[221], [100], [212], [99]
	Hierarchical attention graph convolutional network (HAGCN) [115]	[192], [25]
	Spatio-temporal fusion attention (STFA) [93]	[25], [182]
	Spatio-temporal graph convolutional network (STGCN) [216]	[233], [192]

In this group of papers there is a high variety of benchmarks used, and only few papers share a benchmark model, especially in the GNN category. The most popular benchmarks are two classic well-known machine learning models, the CNN and the LSTM network. Not surprisingly, there are no classical statistical or mathematical benchmark models, since they are more frequently used in forecasting problems compared to classification problems.

Among the GNN benchmarks, there are two models that have been specifically developed for remaining useful life prediction, namely the hierarchical attention graph convolutional network (HAGCN) [115] and the spatio-temporal fusion attention (STFA) [93]. In the HAGCN model, proposed by Li et al. in 2021, the spatial dependencies are modeled by a hierarchical graph representation layer, and a bidirectional long-short term memory network is used for modeling temporal dependencies of sensor measurements. As for the STFA model, proposed by Kong et al. in 2022, it integrates a priori knowledge about the equipment's structure with a spatio-temporal deep learning architecture which employs LSTM cells and an attention mechanism. Neither of the two original papers includes a link to the source code.

5.6.5 Results

The results demonstrate that the proposed GNN models outperform the benchmarks. The accuracy of the models is evaluated using different metrics, depending on whether the context is classification or forecasting. For classification tasks, several studies present confusion matrices and calculate accuracy percentages. For RUL forecasting problems instead, the most commonly used metrics are the RMSE and the score function.

The only results that can be compared across papers are those for the C-MAPSS dataset. Tab. 27 shows the accuracy of the different models, expressed in terms of RMSE and score function.

Table 27: Comparison of the accuracy of the different models on the C-MAPSS dataset on sub-datasets FD001–FD004, expressed in terms of RMSE and score function. The smallest errors are underlined. Numbers from the papers.

Sub-dataset	FD001		FD002		FD003		FD004	
Metrics	RMSE	Score	RMSE	Score	RMSE	Score	RMSE	Score
1D CNN	12.61	273.70	22.36	10412.00	12.64	284.10	23.31	12466.00
2D CNN	18.45	1286.70	30.29	13570.00	19.82	1596.20	29.16	7886.40
AGCNN	12.42	225.51	19.43	1492.76	13.39	227.09	21.50	3392.60
Attention-based LSTM	14.53	322.44	-	-	-	-	27.08	5649.14
ATT-LSTM	13.95	320.00	17.65	2102.00	12.72	223.00	20.21	3100.00
BiGRU-AS	13.68	284.00	20.81	2454.00	15.53	428.00	27.31	4708.00
Bi-LSTM	13.65	295.00	23.18	4130.00	13.74	317.00	24.86	5430.00
BiLSTM-ED	14.74	273.00	22.07	3099.00	17.48	574.00	23.49	3202.00
BLCNN	13.18	302.28	19.09	1557.56	13.75	381.37	20.97	3858.78
CDSG [182]	<u>11.26</u>	<u>188.00</u>	18.13	1740.00	12.03	<u>218.00</u>	19.73	2332.00
ChebyNet-EdgePool	15.21	450.22	16.28	1229.22	14.67	421.02	16.26	<u>1159.74</u>
CNN-LSTM	14.40	290.00	27.23	9869.00	14.32	316.00	26.69	6594.00
ConvGAT [25]	11.34	197.43	<u>14.12</u>	<u>771.61</u>	<u>10.97</u>	235.26	<u>15.51</u>	1231.17
C-Transformer	13.79	475.46	16.11	2214.59	17.10	939.10	19.77	3237.37
DBN	15.21	417.59	27.12	9031.64	14.71	442.43	29.88	7954.51
DCNN	12.61	273.70	22.36	10412.00	12.64	284.1	23.31	12466.00
Earlier CNN	18.45	1287.00	30.29	13570.00	19.82	1596.00	29.16	7886.00
ELM	17.27	523.00	37.28	498149.97	18.90	573.78	38.43	121414.00
GA+RBM+LSTM	12.56	231.00	22.73	3366.00	12.10	251.00	22.66	2840.00
GAT-EdgePool	13.53	309.59	15.07	1380.41	14.66	470.74	17.60	1726.53
GAT-TopkPool	13.21	303.18	17.25	5338.80	15.36	507.52	21.44	2971.93
GB	15.67	474.01	29.09	87280.06	16.84	576.72	29.01	17817.92
GGCN	11.82	186.70	17.24	1493.70	12.21	245.19	17.36	1371.50
HAGCN	11.93	222.30	15.05	1144.10	11.53	240.30	15.74	1218.60
HDNN	13.02	245.00	15.24	1282.42	12.22	287.72	18.16	1527.42
IMDSSN	12.14	206.11	17.40	1775.15	12.35	229.54	19.78	2852.81
LSTM	16.14	338.00	24.49	4450.00	16.18	852.00	28.17	5550.00
LSTMBS	14.89	481.00	26.86	7982.00	15.11	493.00	27.11	5200.00
MODBN	15.04	334.23	25.05	5585.00	12.51	421.91	28.66	6557.00
MS-CNN	11.44	196.22	19.35	3747.00	11.67	241.89	22.22	4844.00
RF	17.91	479.75	29.59	70456.86	20.27	711.13	31.12	46567.63
SBI	13.58	228.00	19.59	2650.00	19.16	1727.00	22.15	2901.00
SMDN	13.40	272.00	-	-	-	-	23.40	4302.00
STFA [93]	11.35	194.44	19.17	2493.09	11.64	224.53	21.41	2760.13
Transformer	13.52	287.07	19.32	1436.74	13.44	263.64	20.38	2784.62

In general, the best results on the different sub-datasets are achieved by the GNN-based comprehensive dynamic structure GNN (CDSG) [182] and convolution-graph attention network (ConvGAT) [25] models.

5.7 Generic

This subsection includes all the papers that do not explicitly address a specific problem. They still present the results on some benchmark case studies, but the related datasets may cover different groups. In particular, the focus is on papers that do not discuss or mention any specific case study prior to the experimental section. The reason for this choice is that they are considered to explore broader methodologies or frameworks that are applied to diverse datasets without a declared focus on a particular case.

5.7.1 Overview

A significant number of papers (24 out of 156) have been categorized under the "Generic" group. The majority of these works commit to address a multivariate time series forecasting problem which is not necessarily limited to a specific field. This "Generic" subset includes one paper from 2021, 4 from 2022, and 19 from 2023, highlighting the recent interest in applying GNNs in more general contexts. These papers are distributed across various journals, with the exception of *Expert Systems with Applications* by Elsevier, *IEEE Transactions on Knowledge and Data Engineering* by IEEE, and *Information Sciences* by Elsevier, each publishing 2 of the selected papers. The majority of authors are affiliated with institutions in China.

5.7.2 Datasets

The selected papers make use of the datasets listed in Tab. 28 in their experiments.

Table 28: List of public datasets in the "Generic" papers and their corresponding links.

Dataset	Used by	Link
Beijing Traffic	[26]	https://github.com/BuaaPercy/Traffic-DataSet-of-Beijing-Road
CCMP wind data	[120]	http://data.remss.com
CI earthquakes	[10]	https://doi.org/10.5194/adgeo-43-31-2016 (source paper)
Chickenpox cases	[10]	https://doi.org/10.48550/arXiv.2102.08100 (source paper)
CW earthquakes	[30]	https://doi.org/10.5194/adgeo-43-31-2016 (source paper)
Electricity consumption	[120], [48], [82], [121], [58], [21], [135], [170], [225], [64]	https://github.com/laiguokun/multivariate-time-series-data
Electricity Consuming Load (ECL)	[189], [88]	https://archive.ics.uci.edu/ml/datasets/ElectricityLoadDiagrams20112014
Electricity transformer Temperature (ETT)	[237], [189], [88]	https://github.com/zhouhaoyi/ETDataset
Energy	[41]	http://dx.doi.org/10.1016/j.enbuild.2017.01.083 (source paper)
Enron	[70]	https://doi.org/10.1073/pnas.1800683115 (source paper)
Eu-Core	[70]	https://doi.org/10.1145/ (source paper)
Exchange-rate	[120], [48], [237], [41], [121], [58], [21], [135], [88], [190], [30], [64]	https://github.com/laiguokun/multivariate-time-series-data
Facebook	[70]	http://networkrepository.com/socfb
GEFCOM 2012	[30]	https://doi.org/10.1016/j.ijforecast.2013.07.001 (source paper)
Hypertext	[70]	http://networkrepository.com/ia-infect-hyper (source paper)

ILI	[237], [88], [30]	https://gis.cdc.gov/grasp/fluview/fluportal dashboard.html
Jena Weather	[237]	https://www.bgc-jena.mpg.de/wetter/
Loan	[70]	https://ai.ppdai.com/mirror/showCompetit ionRisk
METR-LA	[32], [82], [58], [21], [27], [10]	https://paperswithcode.com/dataset/metr-la
MIMIC-III Heart Failure	[61]	https://doi.org/10.1038/sdata.2016.35 (source paper)
MIMIC-III Infection	[61]	https://doi.org/10.1038/sdata.2016.35 (source paper)
MOOC network	[116]	http://snap.stanford.edu/jodie/mooc.csv
Nasdaq	[41], [21]	https://doi.org/10.48550/arXiv.1704.02971 (source paper)
NOAA Weather	[189]	https://www.ncei.noaa.gov/data/local-clima tological-data/
PeMS03	[48]	https://www.kaggle.com/datasets/elmahy/p ems-dataset
PeMS04 (PeMSD4)	[120], [48], [121], [58], [225]	https://paperswithcode.com/dataset/pems04
PeMS08 (PeMSD8)	[120], [48], [121], [58], [225]	https://paperswithcode.com/dataset/pems08
PEMS-BAY	[32], [82], [10]	https://paperswithcode.com/dataset/pems-b ay
PhysioNet	[61]	https://archive.physionet.org/challenge/2012 /papers/
Reddit network	[116]	http://snap.stanford.edu/jodie/reddit.csv
Solar-Energy	[120], [48], [82], [121], [58], [21], [135], [170], [190], [225], [64]	https://github.com/laiguokun/multivariate-t ime-series-data
TAIEX	[26]	https://finance.yahoo.com/
TaoBao	[70]	https://tianchi.aliyun.com/competition/ent rance/
Traffic	[82], [121], [58], [21], [135], [170], [88], [190], [64]	https://github.com/laiguokun/multivariate-t ime-series-data
US stock market price	[30]	https://doi.org/10.48550/arXiv.1810.09936 (source paper)
Wikipedia network	[116]	http://snap.stanford.edu/jodie/wikipedia.csv
Wind-Speed	[237]	https://www.kaggle.com/datasets/fedesorian o/wind-speed-prediction-dataset

It should be noted that there are multiple recurring datasets that can be considered as benchmarks for the community. Some of these have already been discussed in the previous sections. If the results for these datasets have already been shown in previous sections, they will not be repeated again here. Instead, they will be just marked with a star * together with the benchmark models in the tables of the previous sections.

The four most common datasets are Electricity consumption, Exchange-rate, Solar-Energy and Traffic, all available at https://github.com/laiguokun/multivariate-time-series-data. The Electricity consumption dataset contains the hourly electricity consumption in kWh for 321 customers recorded from 2012 to 2014. The Traffic dataset describes the road occupancy rates measured by different sensors on the San Francisco Bay area road network from 2015 to 2016, with an hourly granularity. In Solar energy it is recorded the solar power production from 137 photovoltaic plants in Alabama State in 2006, with a 10 minutes granularity. Finally, Exchange rate contains daily exchange rates of 8 countries including Australia, British, Canada, Switzerland, China, Japan, New Zealand and Singapore, from 1990 to 2016.

In general, the data granularity varies significantly, ranging from fractions of seconds to one week, indicating that there is no particular focus on a specific granularity. Individual papers often cover multiple granularities, and many papers take into account datasets with granularity from 5 minutes to 1 day. As for the forecasting horizon, almost all papers focus on multi-step forecasting, usually considering 12 different forecasting horizons at the same time. Only a few papers mention data pre-processing, and usually utilize min-max or Z-score normalization.

5.7.3 Proposed models

Among the 24 "Generic" papers, 19 use a purely convolutional GNN approach, and two employ a purely attentional model. One paper lacks sufficient detail to determine its classification within the taxonomy [88], and another declares it is using an aggregating approach that is simpler than either convolutional or attentional approaches [135]. One more paper proposes a multivariate time series with dynamic graph neural ordinary differential equations (MTGODE) model, where the continuous dynamics of simplified graph propagation is described by an ordinary differential equation (ODE) [82].

As for the definition of the graph structure, the majority of these models use self-learning techniques. This is a straightforward choice, since all the papers in this section want to ensure the applicability of the model in different contexts, and the use of pre-defined rules for the definition of the graph limits the model's universal applicability. Half of the papers employ a dynamic graph structure, which adapts to the varying temporal patterns observed in the data.

The two most commonly utilized loss functions are the MSE and the MAE. Since the graph structure is typically learned by the models themselves, many papers include a regularization term in the loss function for the optimization of the graph structure (e.g., Refs. [120], [121], [58], [27]).

The majority of the papers specify the language and libraries used for the code, namely Python with PyTorch, PyTorch Geometric [44], and Torch Spatiotemporal [31]. However, only slightly less than half of the papers provide a link to the source code. The links to the code repositories are listed in Tab. 29.

Table 29: List of source codes of the "Generic" models in the review.

Model	Link
Adaptive dependency learning neural network (ADLNN) [170]	https://github.com/AbishekSriramulu/ADLGNN.git
Graph neural network with neural Granger causality (CauGNN) [41]	https://github.com/RRRussell/CauGNN
Gformer [189]	https://github.com/wxh453751461/Gformer
Multi-scale adaptive graph neural network (MAGNN) [21]	https://github.com/shangzongjiang/MAGNN
Multivariate time series deep spatiotemporal forecasting model with a graph neural network (MDST-GNN) [64]	https://github.com/yiminghzc/MDST-GNN
Multivariate time series with dynamic graph neural ordinary differential equations (MTGODE) [82]	https://github.com/GRAND-Lab/MTGODE
Static and dynamic graph learning network (SDGL) [121]	https://github.com/ZhuoLinLi-shu/SDGL
Sparse graph learning from spatiotemporal time series [32]	https://github.com/andreacini/sparse-graph-learning

Temporal decomposition enhanced graph neural network for multivariate time series forecasting (TDG4MSF) [135]	https://github.com/TYUT-Theta/MHZN.git
Temporal graph convolution and attention (T-GAN) [70]	https://github.com/malei666666/T_GAN
Two GNN models with different graph structures [10]	https://github.com/StefanBloemheuvel/graph_comparison

5.7.4 Benchmark models

Tab. 30 displays the benchmark models utilized by at least two of the selected "Generic" papers.

Table 30: List of benchmark models in the "Generic" group divided per category.

Category	Model	Used by
Mathematical and statistical methods	Autoregressive integrated moving average (ARIMA)	[120], [48], [121], [58], [21], [135], [170], [26], [225], [30]
	Gaussian process (GP)	[120], [48], [121], [21], [135], [170]
	Historical average (HA)	[121], [225]
	Vector autoregression (VAR)	[120], [48], [41], [121], [58], [135], [26], [225]
Classical machine learning methods	Autoformer [198]	[48], [237], [88]
	Dual self-attention network for multivariate time series forecasting (DSANet) [71]	[120], [121]
	Feed-forward neural network (FNN)	[26], [30]
	Gated recurrent unit (GRU)	[120], [121], [189], [225], [64]
	Hybrid framework based on fully Dilated CNN (HyDCNN) [117]	[82], [170]
	Informer [243]	[48], [237], [189], [88]
	LogTrans [140]	[189], [88]
	Long-short term memory network (LSTM)	[61], [48], [58], [189], [26], [88], [27], [225], [30]
	Long-short term time series network (LSTNet) [97]	[120], [48], [82], [41], [121], [21], [135], [189], [170], [88], [190], [30], [64]
	Multi-Level Construal Neural Network (MLCNN) [29]	[41], [190]
	Neural basis expansion analysis for interpretable time series forecasting (N-BEATS) [143]	[19], [88]
	Recurrent neural network with fully connected gated recurrent units (RNN-GRU)	[120], [41], [121], [58], [21], [135], [170], [190]
	Reformer [92]	[237], [189], [88]
	SCINet [129]	[48], [64]
	Temporal pattern attention long-short term memory network (TPA-LSTM) [166]	[120], [48], [82], [121], [58], [21], [135], [170], [64]
	Transformer [178]	[61], [41]
	Hybrid of the multilayer perception and autoregressive model (VAR-MLP) [228]	[120], [48], [121], [58], [21], [135], [170], [190], [64]

GNN methods	Adaptive graph convolutional recurrent network (AGCRN) [4]	[120], [48], [121], [58], [21], [225]
	Attention-based spatial-temporal graph convolutional network (ASTGCN) [57]	[121], [58]
	Diffusion convolutional recurrent neural network (DCRNN) [119]	[120], [48], [82], [121], [58], [26], [27], [190], [225]
	Graph auto encoder (GAE) [90]	[116], [70]
	Graph multi-attention network (GMAN) [242]	[120], [82], [27], [225]
	Graph for time series (GTS) [161]	[32], [121]
	Graph WaveNet (GWN) [202]	[48], [82], [58], [21], [27], [190]
	Multivariate time series forecasting with graph neural network (MTGNN) [201]	[32], [120], [48], [82], [121], [58], [21], [135], [170], [27], [190], [225], [64]
	Node2vec [53]	[116], [70]
	Spatial-temporal fusion graph neural network (STFGNN) [114]	[120], [27]
	Spatio-temporal graph convolutional network (STGCN) [216]	[120], [82], [121], [58], [26], [27], [225]
	Spatial-temporal graph ODE networks (STGODE) [43]	[82], [225]
	Spatio-temporal synchronous graph convolutional network (STSGCN) [169]	[120], [48], [121]

There is a wide variety of benchmark models in this "Generic" group. As for mathematical and statistical models, autoregressions and ARIMA models are very popular for their simplicity and interpretability. Among classical machine learning models, the most widely used models are LSTMs, temporal pattern attention long-short term memory network (TPA-LSTM) [166], and long-short term time series network (LSTNet) [97]. The TPA-LSTM model, introduced by Shih et al. in 2019, employs a set of filters to capture time-invariant temporal patterns, and an attention mechanism to identify relevant time series for multivariate forecasting. The source code for this benchmark model is available at https://github.com/gantheory/TPA-LSTM. The LSTNet model, proposed by Lai et al. in 2018, combines a convolution neural network and a recurrent neural network to capture short-term local dependencies among variables and identify long-term patterns. Additionally, it incorporates an autoregressive model that enhances the robustness of the deep learning approach to time series with significant scale fluctuations. The source code for the model is accessible at https://github.com/laiguokun/LSTNet. Among GNN models, the most common ones are DCRNN [119] and MTGNN [201], already discussed in the previous sections.

5.7.5 Results

The most common error metrics used in the evaluation of the models in the "Generic" group are, in order, the mean absolute error (MAE), correlation coefficient (CORR), root mean square error (RMSE), root relative squared error (RRSE), mean absolute percentage error (MAPE), and mean squared error (MSE). Differently from other metrics, where lower values indicate higher accuracy, the correlation coefficient (CORR) quantifies the strength of the the linear relationship between predicted and actual values, with higher values indicating a better performance. This Results subsection compares the results obtained for the Electricity consumption, Exchange rate, Solar energy and Traffic datasets. The results of the proposed models and benchmarks on METR-LA and PEMS datasets were already reported with a * in Subsec. 5.5.5.

Tab. 31 shows the accuracy of the various models applied to the Electricity consumption dataset, which includes data from 1st January 2012 to 31st December 2014 at hourly granularity, for 3, 6, 12 and 24 steps ahead horizons. The accuracy is expressed in terms of RRSE and CORR.

Table 31: Comparison of the average accuracy of the different models on the Electricity consumption dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	
Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
ADLGNN [170]	0.0719	0.9506	0.0809	0.9386	0.0887	0.9312	0.0930	0.9294
AGCRN	0.0766	0.9408	0.0894	0.9309	0.0921	0.9222	0.0967	0.9183
AGLG-GRU [58]	0.0738	0.9434	0.0864	0.9302	0.0912	0.9283	0.0947	0.9274
AR	0.0995	0.8845	0.1035	0.8632	0.105	0.8591	0.1054	0.8595
ARIMA	0.0917	0.8902	0.1002	0.8834	0.1028	0.8604	0.1042	0.8487
Autoformer	0.1258	0.9147	0.1344	0.9001	0.1357	0.8921	0.1554	0.8704
Crossformer	0.0742	0.9452	0.0855	0.9351	0.0901	0.9280	0.0967	0.9205
DSTGN [120]	0.0713	0.9518	0.0821	0.9424	0.0887	0.9357	-	-
DSTIGNN [48]	0.0733	0.9515	0.082	0.9412	0.0899	0.9338	0.0954	0.9289
ESG	0.0718	0.9494	0.0844	0.9372	0.0898	0.9321	0.0962	0.9279
FEDformer	0.0889	0.9321	0.1006	0.9191	0.1154	0.908	0.1202	0.9012
GP	0.1500	0.8670	0.1907	0.8334	0.1621	0.8394	0.1273	0.8818
GTS	0.0790	0.9291	0.0884	0.9187	0.0957	0.9135	0.0951	0.9098
GWN	0.0746	0.9459	0.0922	0.9310	0.0909	0.9267	0.0962	0.9226
HyDCNN	0.0832	0.9354	0.0898	0.9329	0.0921	0.9285	-	-
Informer	0.1337	0.8903	0.1532	0.8705	0.1635	0.8527	0.1834	0.8399
LSTNet	0.0864	0.9283	0.0931	0.9135	0.1007	0.9077	0.1007	0.9119
MAGNN [21]	0.0745	0.9476	0.0876	0.9323	0.0908	0.9282	0.0963	0.9217
MDST-GNN [64]	0.0738	0.9454	0.0833	0.9346	0.0884	0.9264	0.0922	0.9222
MTGNN	0.0745	0.9474	0.0878	0.9316	0.0916	0.9278	0.0953	0.9234
MTGODE [82]	0.0736	0.9430	0.0809	0.9340	0.0891	0.9279	-	-
MTHetGNN	0.0749	0.9456	0.0892	0.9307	0.0959	0.8783	0.0969	0.8782
MTNet	0.0840	0.9319	0.0901	0.9226	0.0934	0.9165	0.0969	0.9147
RNN-GRU	0.1102	0.8597	0.1144	0.8623	0.1183	0.8472	0.1295	0.8651
SARIMA	0.0906	0.9055	0.0999	0.8829	0.1026	0.8674	0.1036	0.8621
SCINet	0.0740	0.9494	0.0845	0.9387	0.0929	0.9305	0.0967	0.927
SDGL [121]	0.0698	0.9534	0.0805	0.9445	0.0889	0.9351	0.0935	0.9301
SDLGNN	0.0726	0.9502	0.082	0.9384	0.0896	0.9304	0.0947	0.9257
SDLGNN-Corr	0.0737	0.9475	0.0841	0.9346	0.0923	0.9263	0.0971	0.9227
STG-NCDE	0.6152	0.8739	0.6584	0.8663	0.7302	0.8728	-	-
TDG4-MSF [135]	0.0731	0.9499	0.0828	0.9371	0.0894	0.9306	0.0969	0.9246
Theta	0.0975	0.8906	0.1029	0.8723	0.1040	0.8576	0.1041	0.8595
TPA-LSTM	0.0823	0.9439	0.0916	0.9337	0.0964	0.9250	0.1006	0.9133
TRMF	0.1802	0.8538	0.2039	0.8424	0.2186	0.8304	0.3656	0.7471
VAR-MLP	0.1393	0.8708	0.1620	0.8389	0.1557	0.8192	0.1274	0.8679

The accuracy of the various models varies depending on the studied forecasting horizon but, overall, one can notice that the GNN models perform better than the others, with the static and dynamic graph learning network (SDGL) [121] being the most accurate.

Tab. 32 presents the accuracy of different models applied to the Exchange rate dataset, with daily data from 1990 to 2016. The evaluation covers horizons of 3, 6, 12, and 24 steps ahead, with accuracy measured by RRSE and CORR.

Table 32: Comparison of the average accuracy of the different models on the Exchange rate dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	
Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
AGCRN	0.0269	0.9717	0.0331	0.9615	0.0374	0.9531	0.0476	0.9334
AGLG-GRU [58]	0.0191	0.9792	0.0233	0.9701	0.0328	0.9548	0.0449	0.9372
AR	0.0228	0.9734	0.0279	0.9656	0.0353	0.9526	0.0445	0.9357
ARIMA	0.0198	0.9754	0.0261	0.9721	0.0344	0.9548	0.0445	0.9301
Autoformer	0.0291	0.9631	0.0379	0.9397	0.0441	0.9201	0.0501	0.9012
Crossformer	0.0226	0.9759	0.0269	0.9656	0.0358	0.9436	0.0489	0.9291
DSTGN [120]	0.0179	0.9782	0.0250	0.9715	0.0346	0.9562	-	-
DSTIGNN [48]	0.0173	0.9818	0.0244	0.9723	0.0333	0.9571	0.0430	0.9407
ESG	0.0181	0.9792	0.0246	0.9717	0.0345	0.9564	0.0468	0.9392
FEDformer	0.0256	0.9701	0.0287	0.9555	0.0379	0.9385	0.0487	0.9190
GP	0.0239	0.8713	0.0272	0.8193	0.0394	0.8484	0.0580	0.8278
GTS	0.0180	0.9898	0.0260	0.9824	0.0333	0.9701	0.0442	0.9518
GWN	0.0251	0.9740	0.0300	0.9640	0.0381	0.951	0.0486	0.9294
Informer	0.0882	0.9563	0.1081	0.9321	0.1301	0.8911	0.1521	0.8021
LSTNet	0.0226	0.9735	0.0280	0.9658	0.0356	0.9511	0.0449	0.9354
MAGNN [21]	0.0183	0.9778	0.0246	0.9712	0.0343	0.9557	0.0474	0.9339
MDST-GNN [64]	0.0172	0.9811	0.0245	0.9727	0.0337	0.9578	0.0431	0.9392
MTGNN	0.0194	0.9786	0.0259	0.9708	0.0349	0.9551	0.0456	0.9372
MTHetGNN	0.0198	0.9769	0.0259	0.9701	0.0345	0.9539	0.0451	0.9360
MTNet	0.0212	0.9767	0.0258	0.9703	0.0347	0.9561	0.0442	0.9388
RNN-GRU	0.0192	0.9786	0.0264	0.9712	0.0408	0.9531	0.0626	0.9223
SARIMA	0.0197	0.9748	0.0253	0.9643	0.0338	0.9495	0.0444	0.9370
SCINet	0.0171	0.9787	0.0240	0.9704	0.0331	0.9553	0.0436	0.9396
SDGL [121]	0.0180	0.9808	0.0249	0.9730	0.0342	0.9583	0.0455	0.9402
TDG4-MSF [135]	0.0172	0.9825	0.0244	0.9718	0.0330	0.9569	0.0433	0.9386
Theta	0.0497	0.9738	0.0257	0.9656	0.0342	0.9510	0.0441	0.9323
TPA-LSTM	0.0174	0.9790	0.0241	0.9709	0.0341	0.9564	0.0444	0.9381
TRMF	0.0351	0.9142	0.0875	0.8123	0.0494	0.8993	0.0563	0.8678
VAR-MLP	0.0265	0.8609	0.0394	0.8725	0.0407	0.8280	0.0578	0.7675

Also in this case, GNN models are the best overall. The discrete graph structure learning for time series model (GTS), proposed in 2021 by Shang et al. in Ref. [161] and used as a benchmark in Ref. [121], demonstrates itself to have a superior performance. It is therefore a suitable benchmark for comparison.

Tab. 33 summarizes the accuracy of the various models on the Solar energy dataset, covering the period from January 1, 2016, to December 31, 2016, at 10-minutes intervals. The analysis considers forecasting horizons of 3, 6, 12, and 24 steps ahead, and the results are expressed in terms of RRSE and CORR.

Table 33: Comparison of the average accuracy of the different models on the Solar energy dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps		6 steps		12 steps		24 steps	

Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
ADLGNN [170]	0.1708	0.9866	0.2188	0.9768	0.2897	0.9551	0.4128	0.906
AGCRN	0.1840	0.9841	0.2432	0.9708	0.3185	0.9487	0.4141	0.9087
AGLG-GRU [58]	0.1762	0.9842	0.2302	0.9682	0.3021	0.9532	0.4130	0.9084
AR	0.2435	0.9710	0.3790	0.9263	0.5911	0.8107	0.8699	0.5314
ARIMA	0.2328	0.9739	0.3413	0.9402	0.4531	0.8886	0.5810	0.8133
Autoformer	0.1935	0.9784	0.2604	0.9651	0.3959	0.9111	0.6064	0.818
Crossformer	0.1758	0.9801	0.2304	0.9679	0.3101	0.9437	0.4115	0.9001
DSTGN [120]	0.1787	0.9867	0.2358	0.9721	0.3079	0.9513	-	-
DSTIGNN [48]	0.1684	0.9869	0.2165	0.9773	0.2863	0.9584	0.4064	0.9118
ESG	0.1708	0.9865	0.2278	0.9743	0.3073	0.9519	0.4101	0.9100
FEDformer	0.1901	0.9827	0.2444	0.9606	0.3502	0.9275	0.4851	0.8876
GP	0.2259	0.9751	0.3286	0.9448	0.5200	0.8518	0.7973	0.5971
GTS	0.1842	0.9842	0.2691	0.9645	0.3259	0.9481	0.4796	0.8678
GWN	0.1773	0.9846	0.2279	0.9743	0.3068	0.9527	0.4206	0.9055
HyDCNN	0.1806	0.9865	0.2335	0.9747	0.3094	0.9515	-	-
Informer	0.2134	0.9715	0.2701	0.9549	0.4331	0.8985	0.7017	0.7921
LSTNet	0.1843	0.9843	0.2559	0.969	0.3254	0.9467	0.4643	0.887
MAGNN [21]	0.1771	0.9853	0.2361	0.9724	0.3015	0.9539	0.4108	0.9097
MDST-GNN [64]	0.1764	0.9855	0.2321	0.9735	0.3082	0.9519	0.4119	0.9103
MTGNN	0.1778	0.9852	0.2348	0.9726	0.3109	0.9509	0.4270	0.9031
MTGODE [82]	0.1693	0.9868	0.2171	0.9771	0.2901	0.9577	-	-
MTHetGNN	0.1838	0.9845	0.2600	0.9681	0.3169	0.9486	0.4231	0.9031
MTNet	0.1847	0.9840	0.2398	0.9723	0.3251	0.9462	0.4285	0.9013
RNN-GRU	0.1932	0.9823	0.2628	0.9675	0.4163	0.9150	0.4852	0.8823
SARIMA	0.2227	0.9760	0.3228	0.9461	0.4512	0.8900	0.5714	0.8184
SCINet	0.1775	0.9853	0.2301	0.9739	0.2997	0.9550	0.4081	0.9112
SDGL [121]	0.1699	0.9866	0.2222	0.9762	0.2924	0.9565	0.4047	0.9119
SDLGNN	0.1720	0.9864	0.2249	0.9757	0.3024	0.9547	0.4184	0.9051
SDLGNN-Corr	0.1806	0.9848	0.2378	0.9722	0.3042	0.9534	0.4173	0.9067
STG-NCDE	0.2346	0.9748	0.2908	0.9605	0.5149	0.8639	-	-
TDG4-MSF [135]	0.1746	0.9858	0.2348	0.9727	0.3082	0.9527	0.4031	0.9143
Theta	0.2442	0.9685	0.3327	0.9445	0.4488	0.8979	0.6092	0.8139
TPA-LSTM	0.1803	0.9850	0.2347	0.9742	0.3234	0.9487	0.4389	0.9081
TRMF	0.2473	0.9703	0.3470	0.9418	0.5597	0.8475	0.9005	0.5598
VAR-MLP	0.1922	0.9829	0.2679	0.9655	0.4244	0.9058	0.6841	0.7149

The results indicate that the dynamic spatiotemporal interactive graph neural network (DSTIGNN) model [48] and the static and dynamic graph learning network (SDGL) model [121] are the most accurate on the solar energy dataset, for shorter and longer time horizons, respectively.

Finally, Tab. 34 illustrates the performance of different models on the Traffic dataset, with hourly data between 2015 and 2016. The accuracy of each model is assessed across 3, 6, 12, and 24 steps ahead horizons, with RRSE and CORR as the evaluation metrics.

Table 34: Comparison of the average accuracy of the different models on the Traffic dataset for 3, 6, 12, and 24 steps time horizons, expressed in terms of RRSE and CORR. The numbers corresponding to the highest accuracy are underlined.

Time horizon	3 steps	6 steps	12 steps	24 steps

Metrics	RRSE	CORR	RRSE	CORR	RRSE	CORR	RRSE	CORR
ADLGNN [170]	0.4047	0.9028	0.4201	0.8928	0.4299	0.8876	0.4416	0.8818
AGCRN	0.4379	0.8850	0.4635	0.8670	0.4694	0.8679	0.4707	0.8664
AGLG-GRU [58]	0.4173	0.8958	0.4722	0.8541	0.4427	0.8755	0.4526	0.8842
AR	0.5991	0.7752	0.6218	0.7568	0.6252	0.7544	0.6300	0.7519
ARIMA	0.5841	0.7959	0.6194	0.7655	0.6197	0.7652	0.6248	0.7610
GP	0.6082	0.7831	0.6772	0.7406	0.6406	0.7671	0.5995	0.7909
GTS	0.4665	0.8695	0.4779	0.8582	0.4792	0.8589	0.4766	0.8573
GWN	0.4484	0.8801	0.4689	0.8674	0.4725	0.8646	0.4741	0.8646
HyDCNN	0.4198	0.8915	0.4290	0.8855	0.4352	0.8858	0.4423	0.8819
LSNet	0.4777	0.8721	0.4893	0.8690	0.4950	0.8614	0.4973	0.8588
MAGNN [21]	0.4097	0.8992	0.4555	0.8753	0.4423	0.8815	0.4434	0.8813
MDST-GNN [64]	0.4162	0.8958	0.4461	0.8803	0.4377	0.8841	0.4452	0.8792
MTGNN	0.4162	0.8963	0.4754	0.8667	0.4461	0.8794	0.4535	0.8810
MTGODE [82]	0.4127	0.900	0.4259	0.8945	0.4329	0.8899	-	-
MTHetGNN	0.4826	0.8643	0.5198	0.8452	0.5147	0.8744	0.5250	0.8418
MTNet	0.4764	0.8728	0.4855	0.8681	0.4877	0.8644	0.5023	0.8570
RNN-GRU	0.5358	0.8511	0.5522	0.8405	0.5562	0.8345	0.5633	0.8300
SARIMA	0.5823	0.7967	0.5974	0.7837	0.6002	0.7811	0.6151	0.7697
SCINet	0.4216	0.8920	0.4414	0.8809	0.4495	0.8772	0.4453	0.8825
SDGL [121]	0.4142	0.9010	0.4475	0.8825	0.4584	0.8760	0.4571	0.8766
SDLGNN	0.4053	0.9017	0.4209	0.8925	0.4313	0.8868	0.4444	0.8801
SDLGNN-Corr	0.4227	0.8937	0.4378	0.8846	0.4576	0.8746	0.4579	0.8784
TDG4-MSF [135]	0.4029	0.9014	0.4196	0.8925	0.4294	0.8864	0.4366	0.8834
Theta	0.6071	0.7768	0.6241	0.7606	0.6271	0.7591	0.6012	0.783
TPA-LSTM	0.4487	0.8812	0.4658	0.8717	0.4641	0.8717	0.4765	0.8629
TRMF	0.6708	0.6964	0.6261	0.7430	0.5956	0.7748	0.6442	0.7278
VAR-MLP	0.5582	0.8245	0.6570	0.7695	0.6023	0.7929	0.6146	0.7891

The accuracy of the models varies by horizon and metric. However, the best one in terms of RRSE over all horizons is the temporal decomposition enhanced graph neural network for multivariate time series forecasting (TDG4MSF) [135].

5.8 Other topics

This final subsection includes 20 papers that fall outside the previously discussed groups. The case studies include cellular traffic prediction, recommendation systems for user preferences, and other forecasting or classification problems. Given the heterogeneity of the papers, only a general overview is provided here, and no comparisons of the approaches or discussions of benchmarks are presented.

5.8.1 Overview

Since GNNs have recently gained considerable popularity, many recent papers focus on applications that do not relate to the categories discussed so far. A frequently discussed topic in this "Other topics" category is cellular traffic prediction ([194], [17], [218]), in terms of SMS messages, calls, internet connections, phone's traffic statistics or locations, which are essential for the cellular network resource management system. Another topic is modulation classification ([181], [208], [3]), which is the process of determining the modulation used at the transmitter based on observations of the received signal [60]. A further area of investigation is the study of user preferences ([235], [83]) to enable personalized experiences and recommendations.

Other applications discussed in the papers of this section are encrypted traffic classification [37], urban spatio-temporal event prediction [81], prediction of the quality of operational processes [232], seismic intensity forecasting [11] (with source code available at https://github.com/StefanBloemheuvel/GCNTimeseriesRegression), prediction of spatio-temporal dynamics with complex structures [197], tailing dam monitoring [158], forecasting of educational video engagement [144], subsurface production forecasting [130], time series prediction for data centers maintenance [163], hydraulic runoff [211], water demand forecasting [222], and human activity recognition [136] (with source code available at https://github.com/riktimmondal/HAR-Sensor).

5.8.2 Datasets

Among the papers selected here, there are only three shared datasets, two for modulation classification and one for cellular traffic prediction. However, the datasets are handled in different ways, either in terms of pre-processing techniques, selected time windows, or train/test split percentages. For this reason, the results of these papers are not directly comparable among each other.

The two datasets for modulation classification used by Refs. [181], [208] and [3] are RML2016.10a (https://www.kaggle.com/datasets/raindrops12/rml201610a, source paper: http://dx.doi.org/10.1007/978-3-319-44188-7_16) and RML2016.10b (https://www.kaggle.com/datasets/marwanabudeeb/rml201610b, source paper: https://pubs.gnuradio.org/index.php/grcon/article/view/11). They include 220,000 and 1.2 million samples respectively, in many modulation types. Each modulation type has 20 levels of signal-to-noise ratios at 2 dB intervals from -20 dB to 18 dB.

As for the cellular traffic prediction dataset used in Refs. [194] and [17], it was proposed by Telecom Italia and MIT Media Lab during the "Telecom Italia Big Data Challenge", and it is available at https://dataverse.harvard.edu/dataverse/bigdatachallenge. The investigated geographical area is divided in a grid, and each cell records the number of SMS messages, calls, and wireless network traffic data in a 10 minutes interval.

6 Discussion

The aim of this SLR is to provide a comprehensive and detailed overview of the use of spatio-temporal GNN models for time series classification and forecasting in various fields, and to assess their performance in different application domains. Existing literature has been collected and synthesized in order to present an overview of datasets, models, and tables of results to support researchers in their future work. In the Introduction two sets of research questions were defined: a generic set and a specific set. Now, the following discussion will answer those research questions. Actually, most of the general research questions were already addressed in the overview presented in Sec. 3. As for the tools, the GNN community mostly uses Python and PyTorch, although some researchers use TensorFlow. Unfortunately, only few papers provide a link to the source code of the proposed model. Almost all papers are funded by public or private entities.

As for the specific questions, the answers are the following.

SQ1 (Applications). The three most investigated fields are, in order, "Mobility", "Environment", and "Generic". Regarding the first two groups, their datasets can be naturally translated into graphs, which explains why they have been studied more extensively over time. In contrast, the "Generic" group has recently gained a significant interest for the applicability to broader contexts. As for the differences between the various fields, the main ones are related to the definition of the graph, which is not always explicit, and the benchmarks used, often related to the mindset of specific communities. It is not easy to compare results across different applications and to determine the most promising fields. The studies in the "Generic" group appear promising across a wide range of domains.

SQ2 (Graph construction). Most of the selected papers focus on pre-defined graph structures (when available), with the objective of extracting the maximum amount of information and enhancing the interpretability of the model. However, there is a recent growing interest in models that learn the graph structure and the edge weights themselves. This trend is expected to become more prevalent in the future.

SQ3 (Taxonomy). As observed in Ref. [223], there are two main approaches to the design of spatio-temporal GNNs: one that treats the spatial and temporal components in separate modules, and one that integrates and processes them together. The analysis of the collected papers reveals that the most common approach in literature is that of separate modules. Specifically, researchers often address the spatial and temporal aspects of the problem independently from each other, and focus on each module separately. The proposed taxonomy of GNN models refers only to the spatial component, and the review indicates that the convolutional and the attentional approaches are the prevalent ones. Approximately 62% of the models are purely convolutional, 25% are purely attentional, and 8% are hybrid convolutional-attentional. With regard to the temporal component, the recurrent structures of GRUs and the attention mechanism are widely used.

SQ4 (Benchmark models). As for the benchmark models, there are many options available, and their choice depends on the specific application. In fields such as energy, Finance, health, and predictive monitoring, the focus tends to be on simpler statistical and classical machine learning benchmarks, with only a limited use of GNN benchmarks. In the "Generic" group, many recent machine learning benchmark models based on the Transformer architecture have emerged. Notably, in "Mobility", "Environment", and "Generic" groups (which are also the most investigated fields), there are many reference GNN benchmark models. The most prevalent benchmarks are the graph convolutional neural network with long-short term memory (GC-LSTM) [154], spatio-temporal graph convolutional network (STGCN) [216], attention-based spatial-temporal graph convolutional network (ASTGCN) [57], diffusion convolutional recurrent neural network (DCRNN) [119], spatio-temporal graph convolutional network (STGCN) [216], and multivariate time series forecasting with graph neural network (MTGNN) [201].

SQ5 (Benchmark datasets). The datasets mentioned in the selected papers are closely related to the specific case of study. Even though some benchmark datasets are listed in the "Generic" group, there is no common standard dataset for the entire GNN research community. It would be beneficial to agreeing on, and start adopting some of the most commonly used datasets such as the traffic ones, with the goal of developing a shared benchmark dataset for the whole research community. Hopefully, this review could serve this purpose by providing comprehensive tables of the results of the models on different datasets to facilitate comparison between spatio-temporal GNN models.

SQ6 (Modeling paradigms). As for the modeling paradigm, most of the selected papers work with a homogeneous graph, which models the relationships among multiple entities of the same nature. This is due to the fact that many basic GNN algorithms were originally developed for homogeneous graphs, and because it is easier to identify relationships between quantities of the same type. Also, in many cases, the focus is on multivariate series where the variables of interest and the target quantities are inherently of the same nature.

SQ7 (Metrics). Regarding the error metrics, their choice is highly dependent on the specific case study. However, the most common ones are mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) for forecasting problems, and accuracy for classification problems.

7 Limits, challenges, and future research directions

In this section the limitations and challenges of spatio-temporal GNN modeling will be discussed, together with directions for further research.

Comparability. As highlighted in Ref. [132], the evaluation of GNN models has improved thanks to the introduction of the Open Graph Benchmark (OGB) [67], which provides a standardized evaluation framework and a variety of benchmark graph datasets. However, there is currently no standardized benchmark for spatio-temporal GNNs. As a result, each model is evaluated on its own selection of datasets, and this fragmentation makes it difficult to compare the results of different studies. To alleviate this problem, this review presented all the information gathered from the selected papers, including datasets, benchmarks, codes, and tables of results. It is intended to serve as a detailed overview and a foundation for further exploration, in the hope that researchers will begin to examine the data collected in the presented tables and, over time, identify relevant datasets and benchmark models.

Reproducibility. The limited availability of links to repositories, source code, and datasets makes it difficult to evaluate the progress of knowledge in spatio-temporal GNNs. Moreover, in many papers the authors do not give detailed information about the model and the graph structure, like definition of the graph, number of nodes, calculation of edge weights. This issues complicate the verification of results and the assessment of the reproducibility of experiments, which are essential to drive further research in this field. Without access to these fundamental resources, it is extremely difficult to assess the accuracy and significance of the proposed models.

Explainability. A crucial aspect of GNN models is explainability, intended as the ability to interpret and understand their decision-making processes. Despite their attempt to explicitly model spatial relationships between series, GNNs are often considered as "black box" models. None of the selected papers adequately tackle the concept of explainability. However, recent literature is beginning to investigate this important topic. For instance, few papers studied perturbation-based explanation methods, which however have proven to be somewhat ineffective as reported in Ref. [180]. Other approaches, such as GNNExplainer [215], aim to identify a small subset of node features that have a crucial role in GNN's predictions. Recently, some researchers have started to explore graph counterfactuals as a means of generating explanations, as reviewed in Ref. [153].

Poor information capacity. Another limitation of GNNs lies in the poor information behind the design of the graph structure and the model definition. A poorly constructed graph with unrepresentative or overly sparse connections, as well as a lack of physical constraints in the equations of the model, can significantly affect the performance. Although efforts have been made to address these issues, such as integrating physical constraints through differential equations, these approaches are not always effective. Therefore, it is essential to develop new techniques to overcome these limitations.

Heterogeneity. The majority of current GNN models are designed to deal with homogeneous graphs, where nodes and edges are all of the same type. As a result, it is challenging to use these GNNs with heterogeneous graphs, which have different types of nodes and edges or different inputs. Therefore, further research is necessary to develop GNN models that can effectively capture the interactions between various types of nodes and edges.

Scalability. Spatio-temporal GNNs are widely used for modeling and analyzing large and complex time series-based network structures. However, GNN models often require a significant amount of memory to compute the adjacency matrix and node embeddings, especially in the case of dynamic graph structures. This scalability challenge results in high computational costs, and in many cases the necessity to use significant GPU resources. Therefore, the development of more scalable GNN models is crucial to facilitate time series analysis even in environments with limited computing power.

8 Conclusions

This paper presented the results of a SLR on the application of spatio-temporal GNN models to time series classification and forecasting problems in different fields. Lately, GNNs have gained significant popularity due to their ability to process graph-structured data. This has led in more recent years to the development of spatio-temporal GNNs in the field of time series analysis, due to their ability to model dependencies between variables and across time points.

This SLR has brought forward on two set of questions: generic questions which can be answered at the level of bibliographic overview, and more specific questions regarding particular aspects of the proposed spatio-temporal GNN models. By answering these questions, it has emerged that the majority of the models in the selected papers is characterized by a convolutional spatial aggregation. However, several graph attentional models are also emerging. In addition, while the majority of the selected papers focus on models with a pre-defined graph structure, an increasing number of studies, particularly in the "Generic" group, are beginning to develop models that learn the graph structure autonomously.

A first key point which results from the presented overview is that the current literature on spatio-temporal GNNs is very fragmented, as it was pictorially reported in Fig. 4. This can be attributed to the fact that the involved researchers come from different communities with focus on specific application domains. As a result, there seems to be a lack of standardised datasets or benchmarks. The objective of this review was also to collect information on datasets, proposed models, links to source codes, benchmarks, and results, in order to provide a foundation for future studies. A second major key point resulting from the proposed SLR seems hence to be that there is a need for the GNN research community to work on common datasets and develop comparable and reproducible models. This would enhance transparency and make it easier to evaluate advancements in the field and to share them more easily.

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A List of selected journal papers

Tab. 35 lists all the journal papers included in this SLR, together with the year of publication, group they belong to, case study, and nature of the task (e.g., classification or forecasting).

Table 35: List of selected journal papers, with year, group they belong to, case study, and nature of the task.

Ref.	Year	Group	Case study	Task
[195]	2023	Energy	Heat load	Forecasting
[229]	2023	Energy	Electricity net load	Forecasting
[191]	2023	Energy	Residential load	Forecasting
[45]	2023	Energy	Electricity load	Forecasting
[34]	2023	Energy	Photovoltaic power	Forecasting
[63]	2022	Energy	Wind power	Forecasting
[167]	2022	Energy	Photovoltaic power	Forecasting
[168]	2022	Energy	Photovoltaic power	Forecasting
[240]	2022	Energy	Power system transient dynamics	Forecasting
[219]	2020	Energy	Wind power	Forecasting
[68]	2022	Energy	Urban buildings energy consumption	Forecasting
[155]	2023	Energy	Solar power	Forecasting
[105]	2022	Energy	Wind power	Forecasting
[22]	2023	Environment	Air quality index	Forecasting
[131]	2023	Environment	PM 2.5 concentration	Forecasting
[171]	2023	Environment	PM 2.5 concentration	Forecasting
[110]	2023	Environment	PM 2.5 concentration	Forecasting
[39]	2023	Environment	Air quality index	Forecasting
[139]	2023	Environment	PM 2.5 concentration	Forecasting
[86]	2023	Environment	PM 2.5 concentration	Forecasting
[151]	2022	Environment	PM 2.5 concentration	Forecasting
[209]	2023	Environment	Sea temperature	Forecasting
[7]	2023	Environment	Wind speed	Forecasting
[101]	2023	Environment	Water quality	Forecasting
[157]	2023	Environment	Wind speed	Forecasting
[236]	2023	Environment	Significant wave height	Forecasting
[87]	2023	Environment	Sea temperature	Forecasting
[8]	2023	Environment	Wind speed	Forecasting
[147]	2023	Environment	Sea temperature	Forecasting
[47]	2023	Environment	Sea temperature	Forecasting
[126]	2022	Environment	Frost	Classification/forecasting
[187]	2022	Environment	Sea temperature	Forecasting
[49]	2021	Environment	Wind speed	Forecasting
[173]	2021	Environment	Sea temperature	Forecasting
[113]	2022	Environment	Water quality	Forecasting
[6]	2023	Environment	Groundwater level	Forecasting
[46]	2023	Environment	Wind speed	Forecasting
[152]	2023	Environment	Rainfall	Forecasting
[40]	2023	Environment	Wind speed	Forecasting
[164]	2023	Environment	Sea temperature	Forecasting
[69]	2022	Finance	Stock prediction	Classification
[149]	2023	Finance	Stock prediction	Classification
[176]	2023	Finance	Stock prediction	Classification
[186]	2023	Finance	Stock prediction	Classification

[111]	2022	Finance	Investment prediction	Forecasting
[174]	2023	Finance	Stock prediction	Classification
[28]	2022	Finance	Financial prediction	Classification
[72]	2023	Finance	Trading	Classification
[214]	2023	Finance	Sale prediction	Forecasting
[19]	2023	Generic	Batch workloads	Forecasting
[116]	2023	Generic	Node classification for websites	Classification
[61]	2023	Generic	Clinical risk	Classification
[32]	2023	Generic	Sensor network	Forecasting
[120]	2023	Generic	Multivariate time series	Forecasting
[48]	2023	Generic	Multivariate time series	Forecasting
[82]	2023	Generic	Multivariate time series	Forecasting
[237]	2023	Generic	Long-term series forecasting	Forecasting
[41]	2023	Generic	Multivariate time series	Forecasting
[121]	2023	Generic	Multivariate time series	Forecasting
[58]	2023	Generic	Multivariate time series	Forecasting
[21]	2023	Generic	Multivariate time series	Forecasting
[135]	2023	Generic	Multivariate time series	Forecasting
[189]	2023	Generic	Multivariate long sequence time series	Forecasting
[170]	2023	Generic	Multivariate time series	Forecasting
[26]	2022	Generic	Multivariate time series	Classification/forecasting
[88]	2023	Generic	Multivariate time series	Forecasting
[27]	2022	Generic	Multivariate time series	Forecasting
[190]	2022	Generic	Multivariate time series	Forecasting
[225]	2023	Generic	Multi-channel time series	Forecasting
[30]	2023	Generic	Multivariate time series	Forecasting
[64]	2022	Generic	Multivariate time series	Forecasting
[10]	2023	Generic	Impact of graph construction	Forecasting
[70]	2021	Generic	Generic	Classification/forecasting
[183]	2023	Health	Epilepsy diagnosis	Classification
[227]	2023	Health	Epidemic prediction	Forecasting
[220]	2023	Health	Epidemic prediction	Forecasting
[118]	2022	Health	Epidemic prediction	Forecasting
[137]	2021	Health	Epidemic prediction	Forecasting
[142]	2022	Health	Epidemic prediction	Forecasting
[234]	2023	Health	Disease diagnosis	Classification
[207]	2023	Health	Clinical risk classification	Classification
[133]	2022	Mobility	Urban traffic	Forecasting
[203]	2021	Mobility	Crowd flow	Forecasting
[185]	2023	Mobility	Flight delays, urban traffic	Forecasting
[102]	2022	Mobility	Crowd flow	Forecasting
[33]	2023	Mobility	Urban traffic	Forecasting
[108]	2022	Mobility	Urban traffic	Forecasting
[107]	2023	Mobility	Urban traffic	Forecasting
[103]	2023	Mobility	Urban traffic	Forecasting
[65]	2023	Mobility	Bus station profiling	Profiling
[193]	2021	Mobility	Passenger demand	Forecasting
[128]	2023	Mobility	Urban traffic	Forecasting

[230]	2022	Mobility	Internet of vehicles	Forecasting
[205]	2020	Mobility	Urban traffic	Forecasting
[127]	2023	Mobility	Urban traffic	Forecasting
[184]	2023	Mobility	Metro flow	Forecasting
[79]	2023	Mobility	Urban traffic	Forecasting
[106]	2023	Mobility	Urban traffic	Forecasting
[95]	2023	Mobility	Urban traffic	Forecasting
[94]	2023	Mobility	Urban traffic	Forecasting
[122]	2023	Mobility	Bike station demand	Forecasting
[210]	2023	Mobility	Urban traffic	Forecasting
[59]	2023	Mobility	Urban traffic	Forecasting
[54]	2023	Mobility	Urban traffic	Forecasting
[124]	2022	Mobility	Taxi demand	Forecasting
[231]	2022	Mobility	Urban traffic	Forecasting
[238]	2022	Mobility	Metro passengers	Forecasting
[85]	2022	Mobility	Urban traffic	Forecasting
[146]	2021	Mobility	Urban traffic	Forecasting
[134]	2022	Mobility	Urban traffic	Forecasting
[241]	2023	Mobility	Urban traffic	Forecasting
[20]	2020	Mobility	Urban traffic	Forecasting
[2]	2021	Mobility	Urban traffic	Forecasting
[13]	2022	Mobility	Urban traffic	Forecasting
[14]	2022	Mobility	Flight delay	Forecasting
[55]	2022	Mobility	Urban traffic	Forecasting
[36]	2023	Mobility	Urban traffic	Forecasting
[15]	2022	Mobility	Urban traffic	Forecasting
[38]	2022	Mobility	Bicycle demand	Forecasting
[77]	2022	Mobility	Urban traffic	Forecasting
[181]	2023	Other	Modulation classification	Classification
[208]	2022	Other	Modulation classification	Classification
[37]	2023	Other	Encrypted traffic classification	Classification
[81]	2022	Other	Spatial temporal events	Forecasting
[232]	2023	Other	Quality indicators	Forecasting
[194]	2023	Other	Cellular traffic	Forecasting
[11]	2023	Other	Seismic data	Forecasting
[197]	2023	Other	Structural dynamics on irregular domains	Forecasting
[158]	2023	Other	Tailing dam monitoring	Forecasting
[144]	2023	Other	Video engagement	Forecasting
[130]	2023	Other	Subsurface production	Forecasting
[17]	2023	Other	Cellular traffic	Forecasting
[163]	2023	Other	Data centers maintenance	Forecasting
[211]	2023	Other	Hydraulic runoff	Forecasting
[235]	2022	Other	App popularity	Forecasting
[218]	2021	Other	Cellular traffic	Forecasting
[222]	2022	Other	Water demand	Forecasting
[83]	2023	Other	User preference	Edge prediction
[136]	2021	Other	Human activity recognition	Classification
[3]	2023	Other	Modulation classification	Classification

[109]	2022	Predictive monitoring	Anomaly detection	Classification
[112]	2023	Predictive monitoring	Anomaly detection	Forecasting
[177]	2023	Predictive monitoring	Fault diagnosis	Classification
[221]	2023	Predictive monitoring	Fault diagnosis	Classification
[100]	2021	Predictive monitoring	Fault diagnosis	Classification
[226]	2023	Predictive monitoring	Fault diagnosis	Classification
[141]	2023	Predictive monitoring	Fault diagnosis	Classification
[233]	2023	Predictive monitoring	Fault prediction	Forecasting
[192]	2023	Predictive monitoring	Remaining useful life	Forecasting
[25]	2023	Predictive monitoring	Remaining useful life	Forecasting
[182]	2023	Predictive monitoring	Remaining useful life	Forecasting
[138]	2021	Predictive monitoring	Remaining useful life	Forecasting
[212]	2022	Predictive monitoring	Remaining useful life	Forecasting
[93]	2022	Predictive monitoring	Remaining useful life	Forecasting
[196]	2023	Predictive monitoring	Remaining useful life	Forecasting
[99]	2023	Predictive monitoring	Fault diagnosis	Classification