GMAN: A Graph Multi-Attention Network for Traffic Prediction

Chuanpan Zheng[1], Xiaoliang Fan[1*], Cheng Wang[1], Jianzhong Qi[2]

[1]Fujian Key Laboratory of Sensing and Computing for Smart Cities, Xiamen University, Xiamen, China

[2]School of Computing and Information Systems, University of Melbourne, Melbourne, Australia

zhengchuanpan@stu.xmu.edu.cn, {fanxiaoliang, cwang}@xmu.edu.cn, jianzhong.qi@unimelb.edu.au

➢ Introduction

The long-term traffic prediction lacks a satisfactory progress in the literature, mainly due to the following challenges.

1) *Complex spatio-temporal correlations.*

- Dynamic spatial correlations.
- Non-linear temporal correlations

2) *Sensitivity to error propagation.*

Small errors in each time step may amplify when predictions are made further into the future.

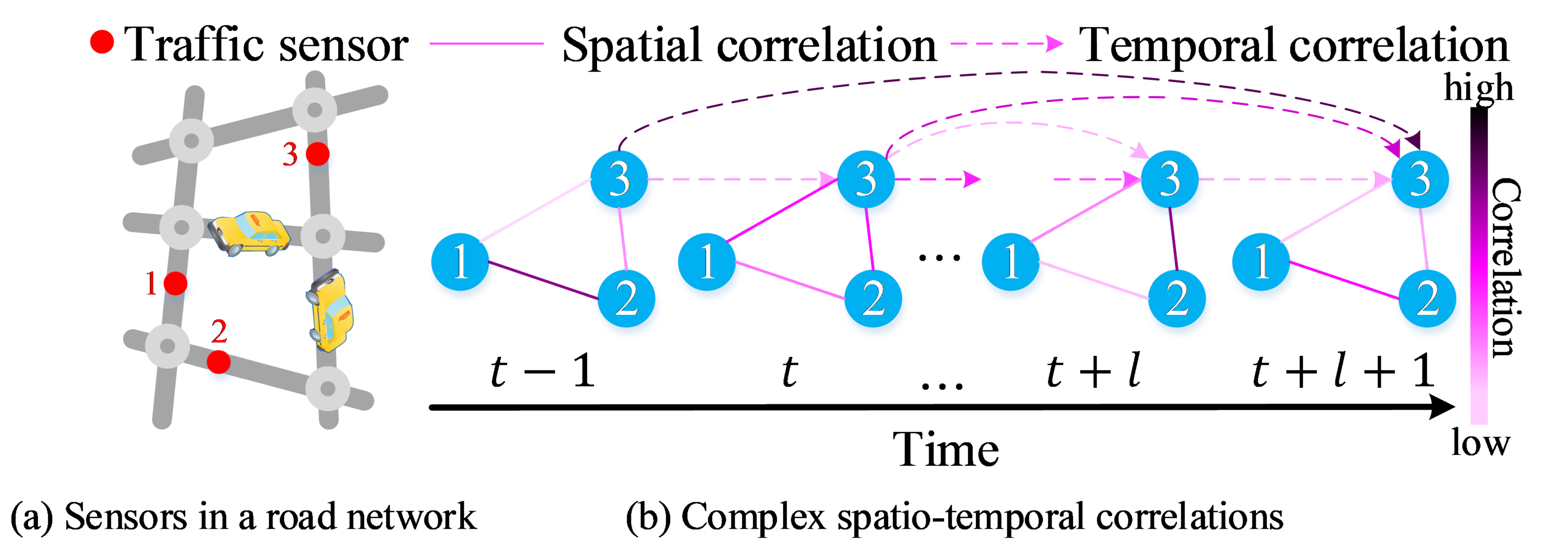

Figure 1: Complex spatio-temporal correlations.

➢ Contributions

- We propose spatial and temporal attention mechanisms to model the dynamic spatial and non-linear temporal correlations, respectively. Moreover, we design a gated fusion to adaptively fuse the information extracted by spatial and temporal attention mechanisms.
- We propose a transform attention mechanism to transform the historical traffic features to future representations. This attention mechanism models direct relationships between historical and future time steps to alleviate the problem of error propagation.
- We evaluate our graph multi-attention network (GMAN) on two real-world traffic datasets, and observe 4% improvement and superior fault-tolerance ability over state-of-the-art baseline methods in the 1 hour ahead prediction. The source code is available at https://github.com/zhengchuanpan/GMAN.

➢ Graph Multi-Attention Network

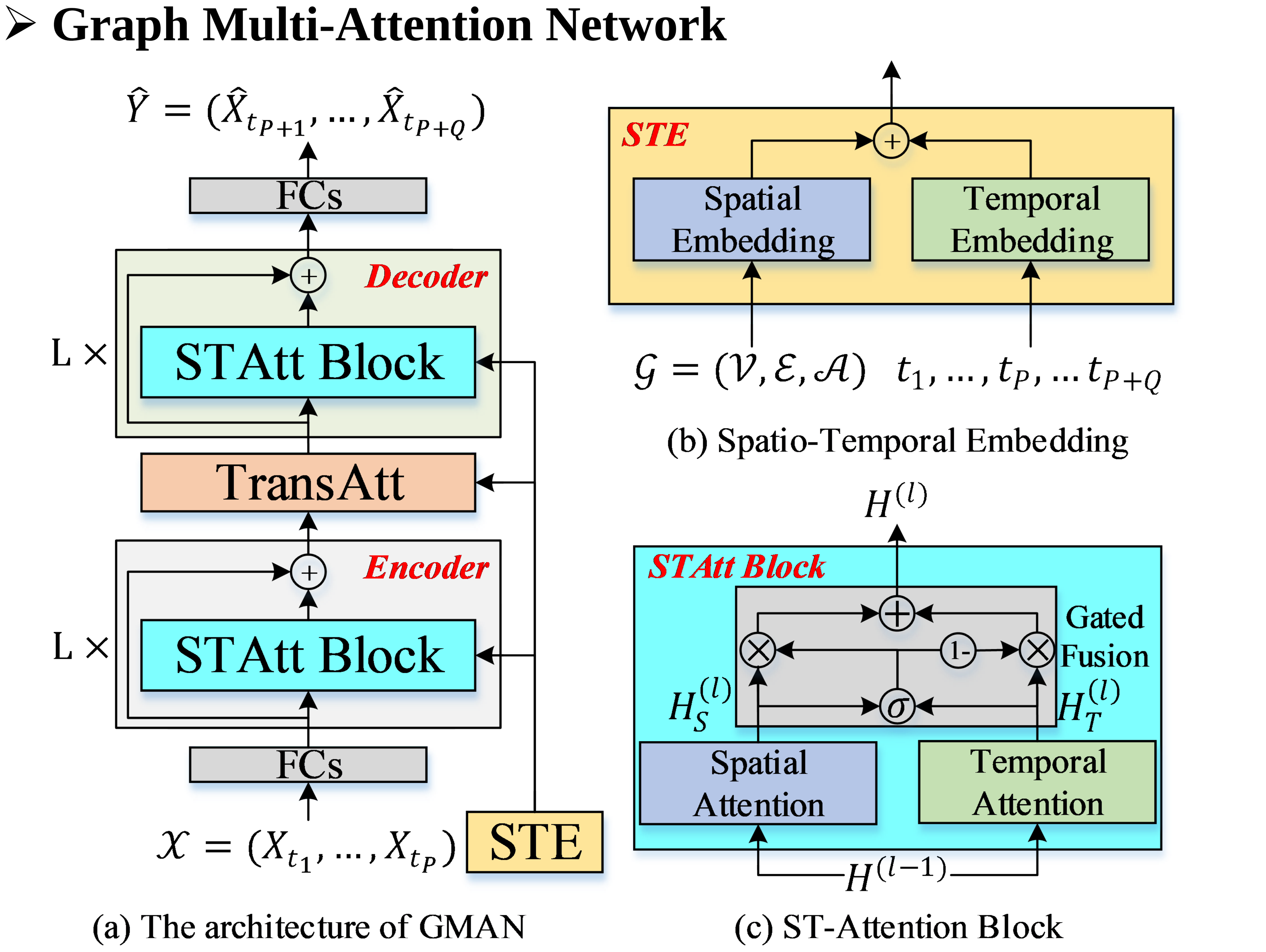

Figure 2: The framework of Graph multi-attention network (GMAN).

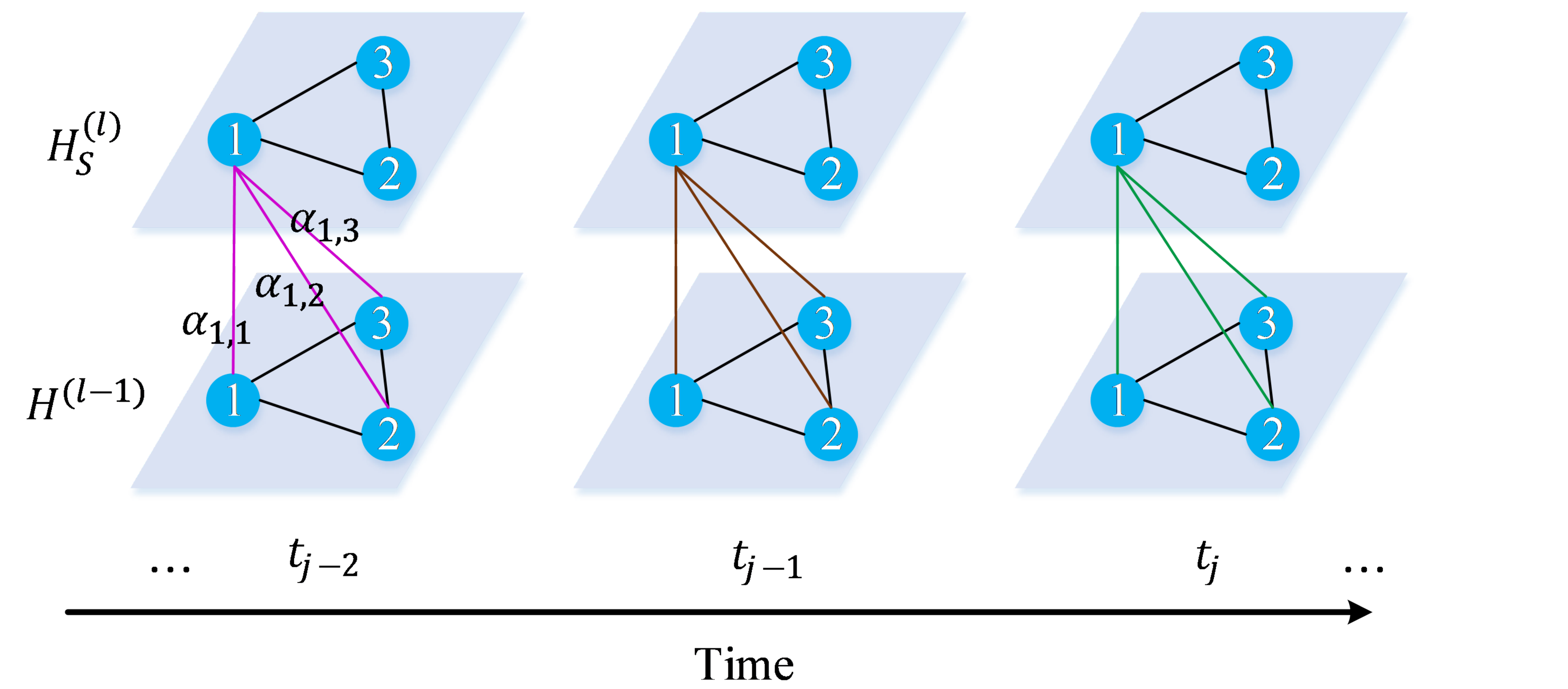

Figure 3: The spatial attention mechanism captures time-variant pair-wise correlations between vertices.

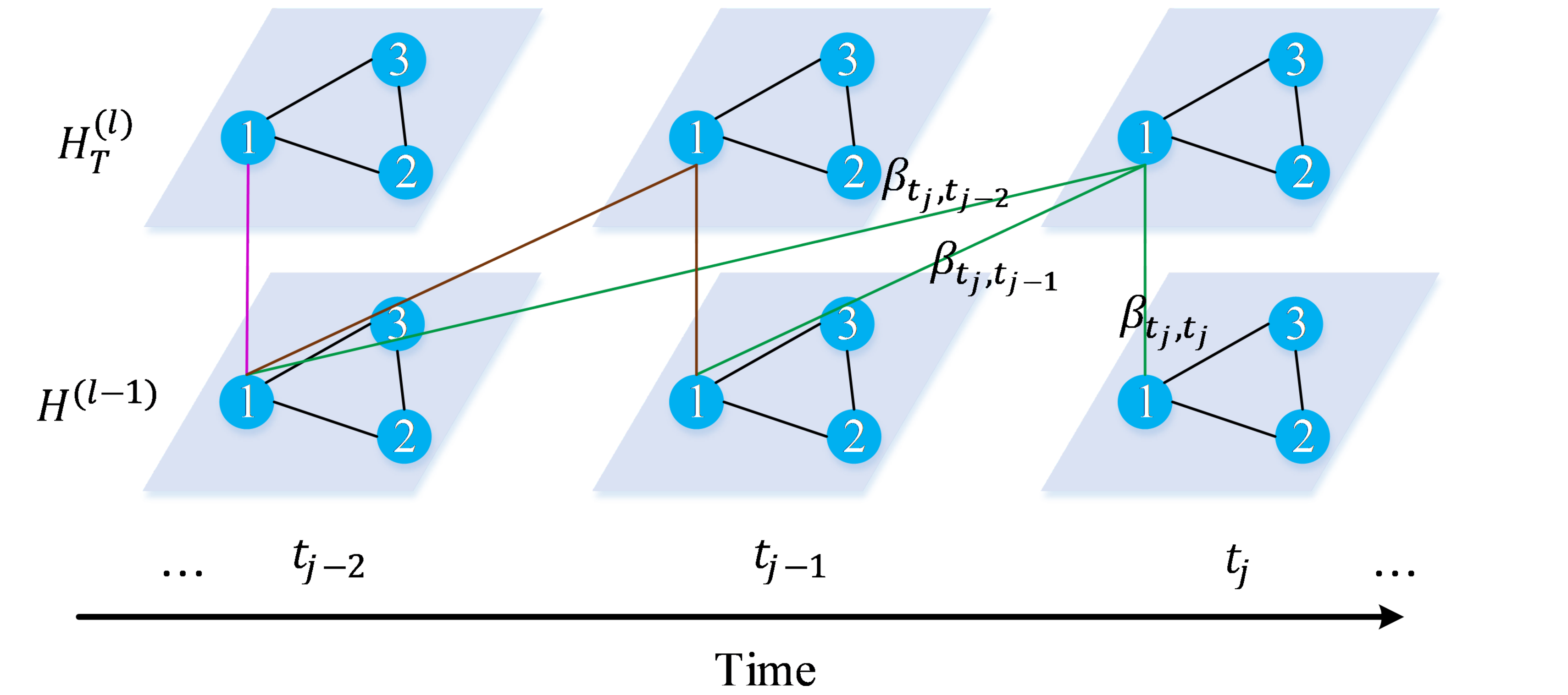

Figure 5: The temporal attention mechanism models the non-linear correlations between different time steps.

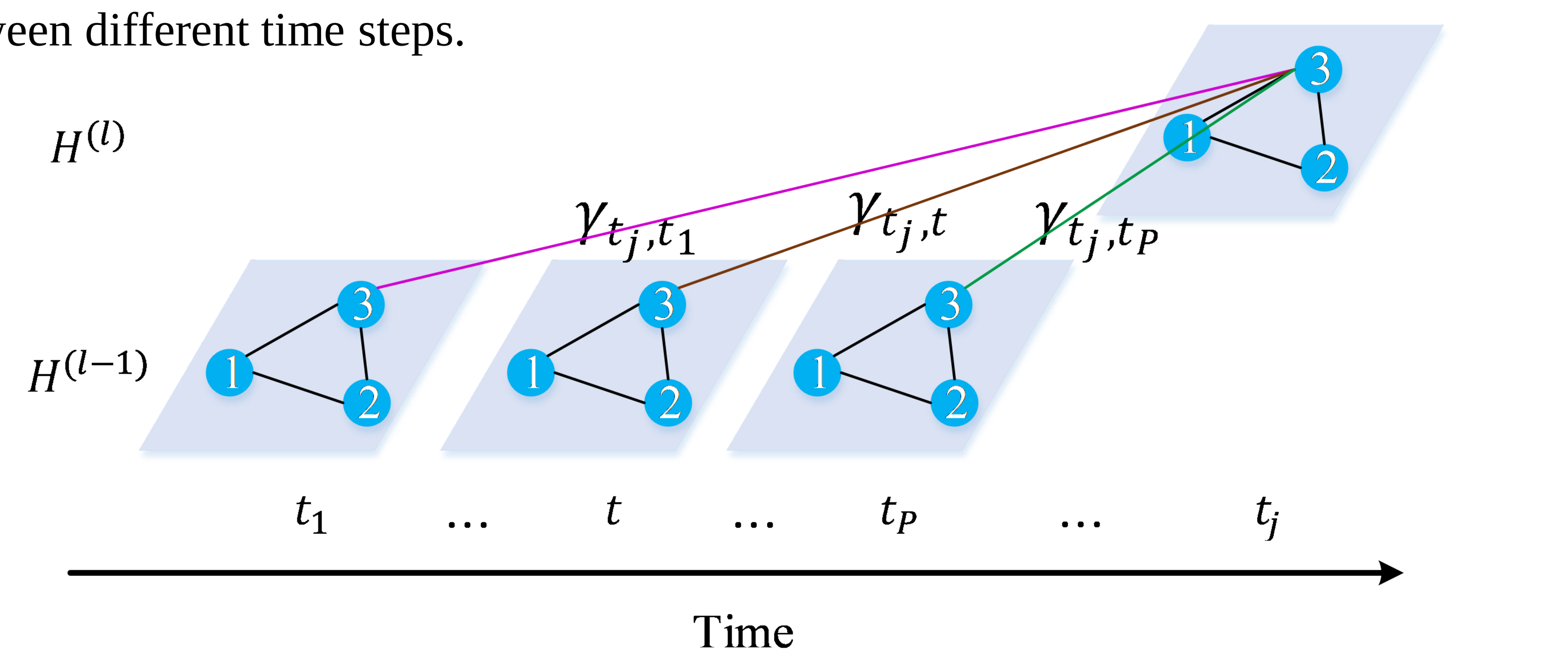

Figure 6: The transform attention mechanism models direct relationships between historical and future time steps.

➢ Experimental Results

Data	Method	15 min			30 min			1 hour		
		MAE	RMSE	MAPE	MAE	RMSE	MAPE	MAE	RMSE	MAPE
Xiamen	ARIMA	14.81	25.03	18.05%	18.83	33.09	22.19%	26.58	46.32	30.76%
	SVR	13.05	21.47	16.46%	15.66	26.34	19.68%	20.69	35.86	26.24%
	FNN	13.55	22.47	16.72%	16.80	28.71	19.97%	22.90	39.51	26.19%
	FC-LSTM	12.51	20.79	16.08%	13.74	23.93	17.23%	16.02	29.57	19.33%
	STGCN	11.76	19.94	14.93%	13.19	23.29	16.36%	15.83	29.40	18.66%
	DCRNN	11.67	**19.40**	14.85%	12.76	22.20	15.99%	14.30	25.86	17.17%
	Graph WaveNet	**11.26**	19.57	**14.39%**	12.06	21.61	15.39%	13.33	24.77	16.50%
	GMAN	11.50	19.52	14.59%	**12.02**	**21.42**	**15.14%**	**12.79**	**24.15**	**15.84%**
PeMS	ARIMA	1.62	3.30	3.50%	2.33	4.76	5.40%	3.38	6.50	8.30%
	SVR	1.85	3.59	3.80%	2.48	5.18	5.50%	3.28	7.08	8.00%
	FNN	2.20	4.42	5.19%	2.30	4.63	5.43%	2.46	4.98	5.89%
	FC-LSTM	2.05	4.19	4.80%	2.20	4.55	5.20%	2.37	4.96	5.70%
	STGCN	1.36	2.96	2.90%	1.81	4.27	4.17%	2.49	5.69	5.79%
	DCRNN	1.38	2.95	2.90%	1.74	3.97	3.90%	2.07	4.74	4.90%
	Graph WaveNet	**1.30**	**2.74**	**2.73%**	1.63	**3.70**	3.67%	1.95	4.52	4.63%
	GMAN	1.34	2.82	2.81%	**1.62**	3.72	**3.63%**	**1.86**	**4.32**	**4.31%**