

Jingru SUN, Chendingying LU, Yichuang SUN, Hongbo JIANG, Zhu XIAO, 2025.
Online transfer learning with an MLP-assisted graph convolutional network for
traffic flow prediction: a solution for edge intelligent devices. *Frontiers of
Information Technology & Electronic Engineering*, 26(9):1692-1710.
<https://doi.org/10.1631/FITEE.2401059>

Online transfer learning with an MLP-assisted graph convolutional network for traffic flow prediction: a solution for edge intelligent devices

Key words: Online transfer learning; Traffic prediction; Intelligent edge devices

Corresponding author: Jingru SUN

E-mail: jt_sunjr@hnu.edu.cn

 ORCID: <https://orcid.org/0000-0001-9474-7778>

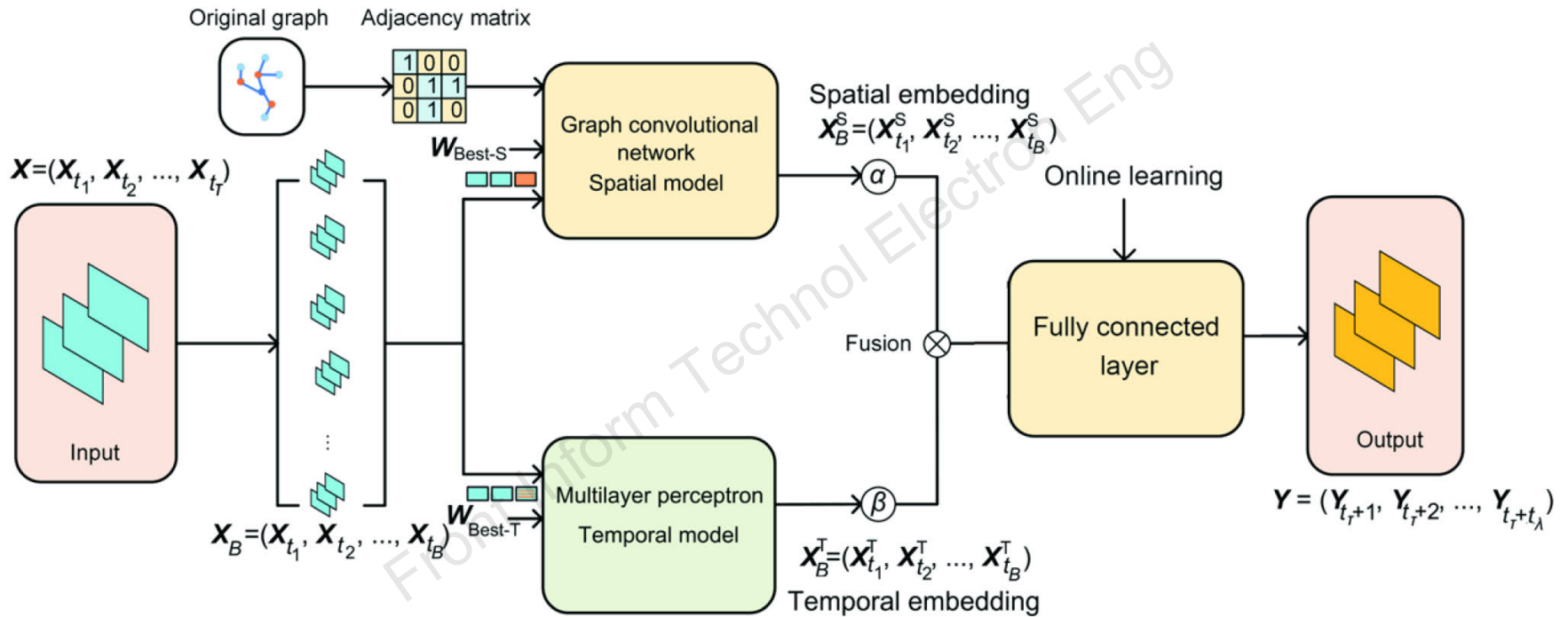
Motivation

1. IoT devices have evolved from simple sensors to intelligent edge systems with integrated sensing, computing, and connectivity. These devices enable real-time monitoring and feedback but face resource limitations, especially in computation. They must balance processing with data transmission, while challenges like traffic flow collection in extreme weather remain.
2. Prediction accuracy is central to traffic flow research. Early models used micro- and macro-simulation, while data-driven and real-time methods grew in the 2010s. Today, deep learning dominates, excelling in spatiotemporal modeling. However, improved accuracy often brings higher algorithmic complexity and longer prediction time.

Main idea

1. We design a lightweight GM by combining multilayer perceptron (MLP) for temporal features with graph convolutional network (GCN) for spatial features, enabling efficient spatiotemporal modeling on edge devices.
2. We integrate GM with an online transfer learning (OTL) framework to ease resource use while keeping accuracy through compact models with small distances.
3. We validate OTL on PeMS04 with faster convergence, marking the first use of OTL in traffic prediction.

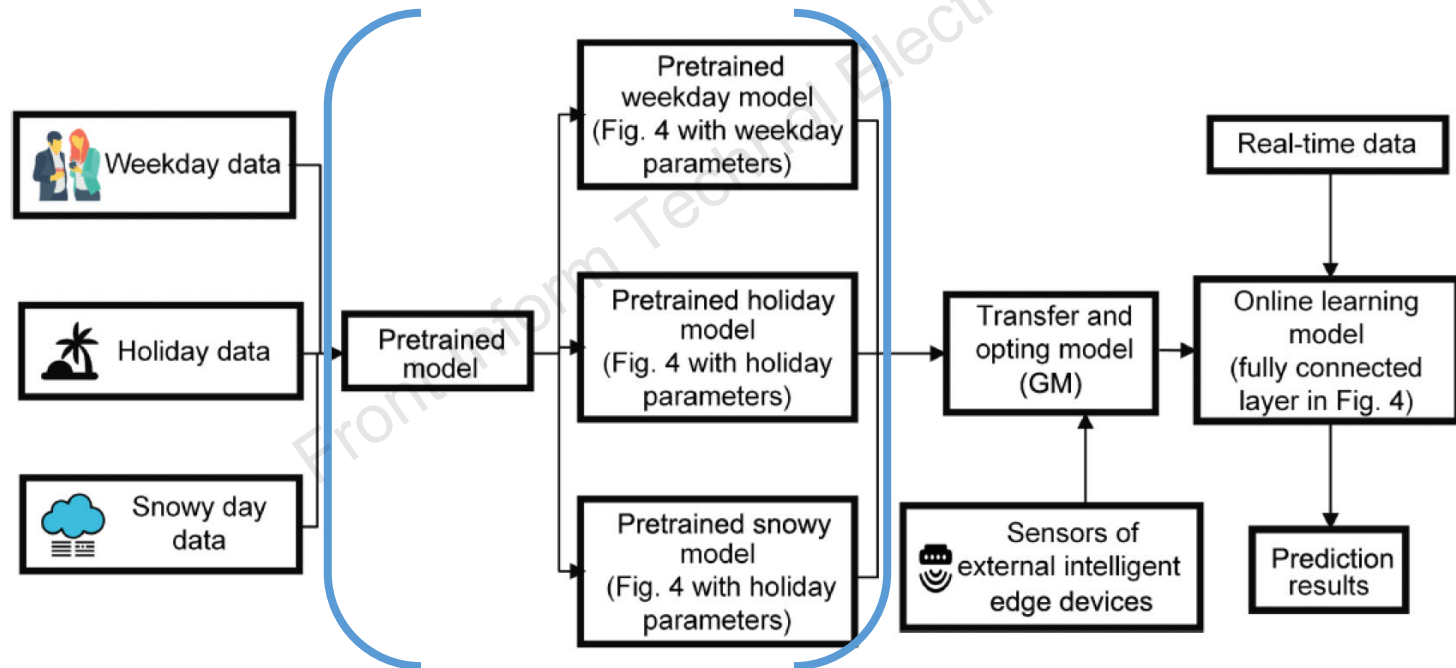
Framework



Overview of the MLP-assisted graph convolutional network (GM)

Method

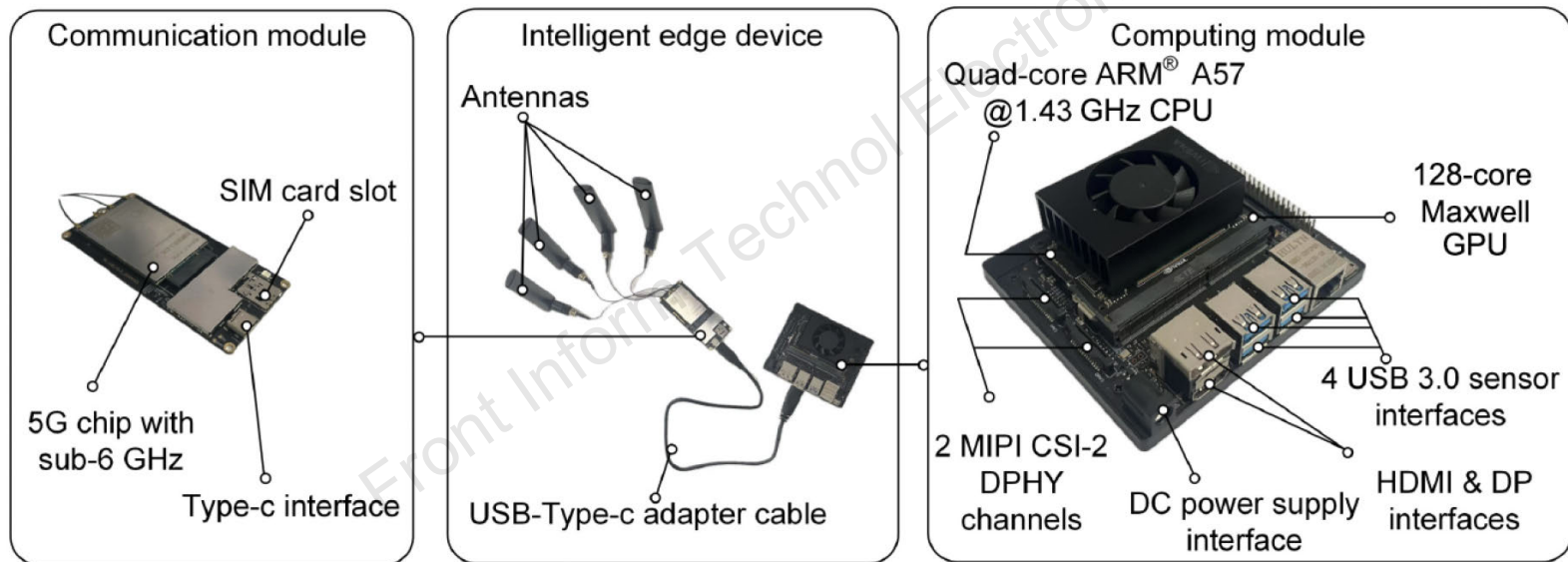
1. We train the model with classified datasets to evaluate convergence time and performance using MAE, MAPE, and RMSE.



OTL framework and data flow

Method

2. The edge device computes Euclidean distances with real-time data and selects the closest pretrained model.



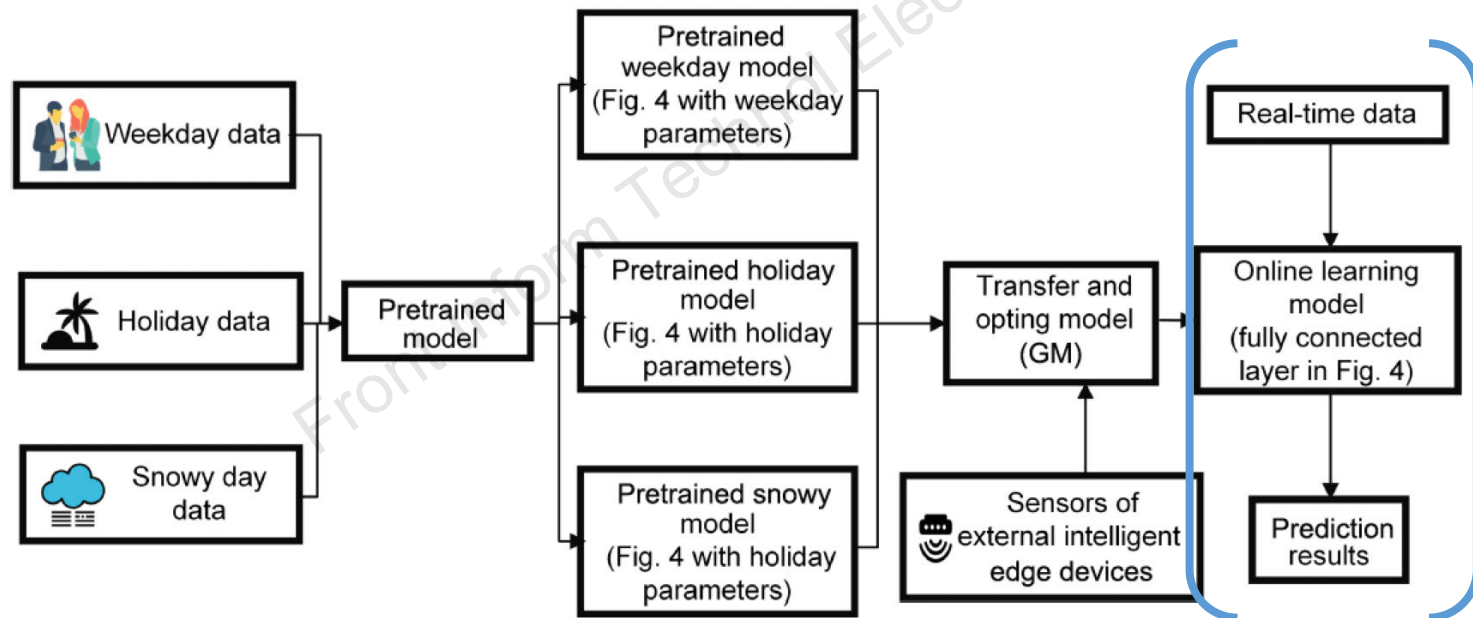
Edge device

$$d(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

Euclidean distances

Method

3. After loading the transferred model, we freeze feature layers and perform online learning on the fully connected layer, adjusting its learning rate until convergence.



Major results

Table 7 Metrics of all methods on PeMS04 (weekday), PeMS04 (holiday), and PeMS04 (weather)

Method	PeMS04 (weekday)				PeMS04 (holiday)				PeMS04 (weather)			
	MAE	MAPE (%)	RMSE	Time (s)	MAE	MAPE (%)	RMSE	Time (s)	MAE	MAPE (%)	RMSE	Time (s)
HA	48.42	38.55	65.43	90.35	33.57	27.99	53.11	48.85	40.52	48.23	60.23	26.16
GCN	46.92	36.75	62.69	96.90	29.63	32.40	42.29	32.33	35.09	27.73	49.77	19.17
VAR	25.62	21.58	38.02	89.26	20.46	17.25	31.18	48.37	26.32	27.47	39.22	20.63
MLP	24.77	18.36	36.28	69.38	25.52	18.60	38.29	21.48	29.62	36.57	39.03	12.14
DCRNN	23.56	16.28	35.62	68.58	23.43	17.43	37.24	42.24	28.42	32.46	36.12	18.33
STGCN	22.64	15.08	36.64	70.58	24.38	16.42	38.25	40.25	27.56	31.45	36.14	19.58
AGCRN	21.88	13.43	35.21	72.33	22.34	15.52	34.26	50.25	26.28	29.43	32.48	20.69
Cy2Mixer	21.74	13.08	33.44	123.56	21.85	15.18	33.18	80.33	25.98	30.14	38.23	25.48
STAEformer	21.78	12.96	34.02	111.35	21.98	15.27	34.01	76.48	26.03	29.00	38.88	23.19
GM	22.27	15.69	33.28	75.91	23.27	18.97	33.07	39.25	34.60	35.93	49.74	19.37
OTL-HA	34.52	34.23	47.44	14.02	32.54	27.93	50.85	5.56	37.49	45.72	55.42	14.02
OTL-GCN	32.12	26.27	45.96	13.00	29.25	32.21	41.73	4.12	33.28	26.01	47.42	13.28
OTL-VAR	24.52	17.43	30.02	15.52	20.12	17.02	30.25	5.02	23.98	26.17	37.85	15.52
OTL-MLP	24.55	16.58	35.86	16.01	25.23	18.45	34.74	5.93	26.77	31.08	36.23	2.79
OTL-DCRNN	22.98	14.18	31.52	9.65	23.01	17.21	35.98	3.58	26.47	32.18	34.12	8.32
OTL-STGCN	22.53	14.02	32.28	7.56	23.95	15.89	37.52	3.99	25.74	27.93	34.38	6.78
OTL-AGCRN	19.24	12.44	29.51	5.43	19.25	15.03	29.21	2.35	23.58	21.49	31.51	4.3
OTL-Cy2Mixer	19.10	12.28	30.18	28.12	18.14	14.33	28.20	13.34	23.33	22.65	37.78	18.63
OTL-STAEformer	19.19	12.01	29.41	20.55	18.23	14.02	29.01	10.56	23.46	20.38	37.62	17.32
ST-GFSL	19.23	13.89	29.34	113.35	18.41	16.56	29.13	57.43	23.38	24.51	36.47	68.43
ST-DAAN	19.14	13.31	29.28	98.72	18.33	15.15	28.00	65.43	23.35	23.31	34.58	80.72
OTL-GM	19.25	14.09	29.04	4.93	18.38	15.14	28.18	2.20	25.54	26.09	36.26	1.10

The best results are in bold

Conclusions

1. This paper addresses two major challenges in real-world traffic flow prediction within the IoT context: limited computational resources on intelligent edge devices and data sparsity caused by extreme weather conditions.
2. Extensive experiments and ablation studies on the PeMS04 dataset confirmed that OTL-GM effectively addresses both computational resource constraints and data sparsity on edge devices.
3. The proposed approach enhances the practical value of traffic flow prediction and offers a feasible solution for edge computing environments.



Jingru SUN received the Ph.D. degree in computer science and technology from Hunan University, Changsha, China, in 2014. She is currently an Associate Professor with the College of Computer Science and Electronic Engineering, Hunan University. She has published more than 20 articles. Her research interests include intelligent transportation, memristors, and their application to storage and neural networks.



Chendingying LU received the B.E. and M.E. degrees from the School of Information Science and Engineering, Hunan University, Changsha, China, in 2022 and 2025, respectively. His research interests include deep learning, data mining, and traffic flow prediction.



Zhu XIAO (Senior Member, IEEE) received the M.S. and Ph.D. degrees in communication and information systems from Xidian University, China, in 2007 and 2009, respectively. From 2010 to 2012, he was a research fellow with the Department of Computer Science and Technology, University of Bedfordshire, U.K. He is currently a full professor with the College of Computer Science and Electronic Engineering, Hunan University, China. He is serving as an associated editor of *IEEE Trans Intell Transp Syst*. His research interests include wireless localization, Internet of Vehicles, and intelligent transportation systems.



Hongbo JIANG received the Ph.D. degree from Case Western Reserve University, in 2008. He is currently a full professor with the College of Computer Science and Electronic Engineering, Hunan University. He was an editor of *IEEE/ACM Trans Network*, an associate editor of *IEEE Trans Mob Comput*, and an associate technical editor of *IEEE Commun Mag*. He is an elected member of Academia Europaea, and fellow of IET, BCS, and AAIA. His research interests include concerns computer networking, especially algorithms and protocols for wireless and mobile networks.



Yichuang SUN received the B.S. and M.S. degrees in communications and electronics engineering from Dalian Maritime University, Dalian, China, in 1982 and 1985, respectively, and the Ph.D. degree in communications and electronics engineering from the University of York, York, U.K., in 1996. He is currently a Professor of Communications and Electronics, Head of the Communications and Intelligent Systems Research Group, and Head of the Electronic, Communication, and Electrical Engineering Division, School of Engineering and Computer Science, University of Hertfordshire, Hatfield, U.K. He has published over 350 articles and contributed 10 chapters in edited books. He has also published four text and research books: Continuous-Time Active Filter Design (CRC Press, USA, 1999), Design of High Frequency Integrated Analogue Filters (IEE Press, U.K., 2002), Wireless Communication Circuits and Systems (IET Press, 2004), and Test and Diagnosis of Analogue, Mixed-Signal and RF Integrated Circuits: The Systems on Chip Approach (IET Press, 2008). His research interests include wireless and mobile communications, RF and analogue circuits, micro-electronic devices and systems, machine learning, and deep learning.