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Train Time Delay Prediction for High-speed Train Dispatching Based on Spatio Temporal Graph Convolutional Network

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ABSTRACT

Railway operations involve different types of entities (stations, trains, etc.), making the existing graph/network models with homogenous nodes (i.e., the same kind of nodes) incapable of capturing the interactions between the entities. This paper aims to develop a heterogeneous graph neural network (HetGNN) model, which can address different types of nodes (i.e., heterogeneous nodes), to investigate the train delay evolution on railway networks. To this end, a graph architecture combining the HetGNN model and the GraphSAGE homogeneous GNN (HomoGNN), called SAGE-Het, is proposed. The aim is to capture the interactions between trains, trains and stations, and stations and other stations on delay evolution based on different edges. In contrast to the traditional methods that require the inputs to have constant dimensions (e.g., in rectangular or grid-like arrays) or only allow homogeneous nodes in the graph, SAGE-Het allows for flexible inputs and heterogeneous nodes. The data from two sub-networks of the China railway network, namely the Guangzhou South network (GZS-Net) and the Changsha South network (CSS-Net), are applied to test the performance and robustness of the proposed SAGE-Het model. The experimental results show that SAGE-Het exhibits better performance than the existing delay prediction methods and some advanced HetGNNs used for other prediction tasks; the predictive performances of SAGE-Het under different prediction time horizons (10/20/30 min ahead) all outperform other baseline methods; the accuracies are over 90% under the permissible 3-minute errors for the three prediction time horizons. Specifically, the influences of train interactions on delay propagation are investigated based on the proposed model. The results show that train interactions become subtle when the train headways increase (e.g., when the train headways are over 20 min, canceling the edges does not decrease the prediction performance). This finding directly contributes to decision-making in the situation where conflict-resolution or train-canceling actions are needed.

Keywords: Heterogeneous graph neural network, GraphSAGE, Railway network, Delay evolution; Train interactions.

I. INTRODUCTION

Railway networks are complex systems consisting of multitudinous fixed facilities, including stations and tracks, and moving objects, most notably trains. The states of running trains are a result of interactions between the facilities and objects in the systems, as well as the effects of the external environment, such as bad weather. (Huang et al., 2020b; Wang and Zhang, 2019). As a measurement of the deviation between the actual and scheduled operation plans, delays are generally used to describe the state of a railway network, where trains are the most common moving objects in the system. As such, the delays of running trains are great indicators to evaluate the state of a railway network. Network-oriented train delay evolution is thus critical for railway operators and controllers as a comprehensive understanding of train delays in the network improves the quality of traffic control actions and rescheduling strategies (Sciences, 2018; Wen et al., 2019). Due to the availability of data, numerous state-of-the-art machine-learning methods have been used in railway systems (Oneto et al., 2017; Ye et al., 2021). Among them, delay prediction or propagation is a popular field. However, the majority of previous delay prediction and propagation research is train-oriented (Huang et al., 2020b; Marković et al., 2015); in other words, they concentrated mainly on trains and forecasted the delays of each train in the downstream stations. However, in practice, dispatchers need to pay more attention to the network states from a systematic perspective, i.e., the delays of the railway network. In this study, we model train delays from a network perspective, considering the different kinds of trains and stations in the systems. The proposed network-oriented approach considers all trains at each moment, and explore the evolution of railway network delay, by predicting the delays of the running trains in the network after a given time interval. The network-oriented approach is expected to support dispatchers with a more comprehensive understanding of the state of the entire railway network, thus enabling them to make a global, rather than partial, adjustment plan.

II. RELATED WORK

Some achievements have been made in the prediction of train delay previously. Generally, it can be divided into the following categories: (1) works based on scenario calculation and simulation data; (2) works based on actual data without considering the spatiotemporal characteristics of train operation; (3) works based on actual data and considering external factors but ignoring the spatiotemporal characteristics of train operation; (4) works based on the actual performance data, considering the spatiotemporal characteristics of train operation but ignoring the external factors. Some studies are not based on actual train operation data. For example, Wang et al. [15] analyzed the four aspects of people, equipment, environment, and management and further selected 14 main influencing factors of train delay; the interpretive structure model is used to analyze the train delay. Based on scenario calculation, Ma [16] analyzed the influencing factors of train delay degree and calculated the corresponding weight through expert scoring method and analytic hierarchy process, solved the models of different scenarios by introducing genetic factor and information entropy, and solved the train operation adjustment model by example simulation, so as to adjust and optimize the train delay model.

Some studies are based on actual performance data but do not consider the spatiotemporal characteristics of the train. For example, Huang et al. [17] put the delay time of the train at the initial late station, the total delay time of train passing through each station, and the total interval buffer time for each stop, as well as the 0-1 variable that identifies whether the train is delayed through the Zhuzhou WestChangsha South interval as independent variables, and used random forest regression to predict train delays. Oneto et al. [18] proposed a fast learning algorithm for shallow and deep extreme learning machines based on the useful and actionable information in a large amount of historical train operation data of the Italian railway network and made full use of the recent memory scale data processing technology to predict train delays.

Some studies consider external factors but do not consider the spatiotemporal characteristics. For example, the research of Oneto et al. [19] does not use the historical data of train operation but uses the static rules established by railway infrastructure experts based on classical univariate statistics and uses the weather information provided by the national meteorological service to further improve the model. ,e train operation data changes with time and space. ,e model that only depends on the rules defined by experts has poor flexibility and portability, and it is hard to grasp the train operation law in the data.

III. PROPOSED SYSTEM

Train operation data is typical spatiotemporal network data [5]. In the real high-speed railway network, the operation of trains has a strong spatial dependence, temporal relevance, and spatiotemporal correlation. Spatial dependence is the direct influence between adjacent stations. ,e number of train delays at the next station will be affected by the delays at the previous station. Temporal relevance refers to the fact that the delay of a certain time period at a certain station has the same trend as that in the past few days and weeks. Spatiotemporal correlation refers to the fact that, in the spatial dimension, the mutual influence between different stations is different. Even the same station has different effects on its adjacent stations over time, and, in the time dimension, the historical observation data of different stations have different effects on the delay status of the station and its adjacent stations at different times in the future; therefore, the train operation data of high-speed railway shows strong dynamic correlation in spatiotemporal dimension. ,is paper uses three ways to sample data: the latest time series (by hour) and the time series of one day and one week. Weather conditions and major holidays also have dual attributes in time and space. From the perspective of temporal dimension, for a special station, the change of weather in a week will be greater than that in a day, and the change in a day will be greater than that in each hour. From the perspective of spatial dimension, in the same time period, different stations have different weather. For example, theweather conditions between closer stations will be more same, while the weather conditions of stations farther away will be more different. ,erefore, we believe that weather factors have spatiotemporal characteristics. For major holidays, we believe that the major holiday factors have the temporal characteristics.

IV. CONCLUSION

Focusing on the spatiotemporal and dynamic correlation of high-speed railway train operation data, this paper constructs MATGCN model based on multiattention mechanism to predict the train delay at high-speed railway stations. ,is model combines multiattention mechanism and spatiotemporal convolution, including spatial dimension graph convolution and temporal dimension standard convolution, to capture the spatiotemporal characteristics of train operation data at the same time, and adds multifeature attention mechanism to process the external factors such as weather conditions, wind level, and major holiday to achieve more accurate prediction. In the experimental stage, we compare and evaluate the MATGCN model proposed in this paper with the ANN, SVR, LSTM, RF, and TSTGCN models and use MAE, RMSE, and MAPE to evaluate the prediction effect of the model. ,e result shows that the three attention mechanisms play a positive role in improving the performance of the model.

V. REFERENCES

[1] Z. Jiang and Q. Miao, "Delay Influence and Its Mitigation Measures of Train Operation in Urban Rail Transit," Modern Urban Transit, vol. 5, 2009.

[2] Y. Feng, "High Speed Railway Delay Forecasting Method Based on Artificial Neural network," Southwest Jiaotong University, Chengdu, China, 2019.

[3] Y. Yu, Y. Zhang, S. Qian, and Y. Hu, "A Low Rank Dynamic Mode Decomposition Model for Short-Term Traffic Flow prediction," IEEE Transactions on Intelligent Transportation Systems, vol. 22, 2020.

[4] J. Wang, Y. Zhang, Y. Wei, and Y. Hu, "Metro Passenger Flow Prediction via Dynamic Hypergraph Convolution Networks," IEEE Transactions on Intelligent Transportation Systems, vol. 22, 2021.

[5] P. Huang, C. Wen, L. Fu, Q. Peng, and Y. Tang, "A deep learning approach for multi-attribute data: a study of train delay prediction in railway systems," Information Sciences, vol. 516, pp. 234–253, 2020.

[6] Y. Wang, Y. Zhang, X. Piao, and Y. Hu, "Traffic data reconstruction via adaptive spatial-temporal correlations," IEEE Transactions on Intelligent Transportation Systems, vol. 20, no. 4, pp. 1531–1543, 2018.

[7] J. Ludvigsen and R. Klæboe, "Extreme weather impacts on freight railways in Europe," Natural Hazards, vol. 70, no. 1, pp. 767–787, 2014.

[8] Y. Li and R. Yu, "Diffusion Convolutional Recurrent Neural Network: Data-Driven Traffic Forecasting," GitHub, 2018, https://github.com/liyaguang/DCRNN.

[9] Y. Liu, J. Guo, C. Luo, and L. Meng, "Big data analysis and application prospect of train operation performance," CHINA RAILWAY, vol. 000, no. 6, pp. 70–73, 2015.

[10] S. Milinkovi ́c and M. Markovi ́c, "A fuzzy Petri net model to estimate train delays," Simulation Modelling Practice and (eory, vol. 33, pp. 144–157, 2013.

[11] N. Markovic and S. Milinkovi ́ c, "Analyzing passenger train arrival delays with support vector regression," Transportation Research Part C: Emerging Technologies, vol. 56, pp. 251–262, 2015.

[12] J. Lessan, L. Fu, and C. Wen, "A hybrid Bayesian network model for predicting delays in train operations," Computers & Industrial Engineering, vol. 127, pp. 1214–1222, 2019.

[13] D. Zhang, Y. Peng, and Y. Zhang, "Train Time Delay Prediction for High-Speed Train Dispatching Based on SpatioTemporal Graph Convolutional Network," IEEE Transactions on Intelligent Transportation Systems, 2021.

[14] D. Zhang, Y. Peng, and Y. Xu, "A High-Speed Railway Network Dataset from Train Operation Records and Weather Data," Figshare. Dataset., https://doi.org/10.6084/m9.figshare. 15087882.v3, 2021.

[15] J. Wang, Y. Peng, and J. Lu, "Ism-based analysis of causes of train delay," CHINA RAILWAY, vol. 000, no. 001, pp. 48–52, 2020.
[16] Q. Ma, "Research on Adjustment and Optimization of Train Delay Based on Scenario Computing," Lanzhou Jiaotong University, Lanzhou, China, 2016.
[17] P. Huang, Q. Peng, and C. Wen, "Random forest prediction model for Wuhan-Guangzhou HSR primary train delays recovery," Journal of the China Railway Society, vol. 40, no. 7, pp. 1–9, 2018.
[18] L. Oneto, E. Fumeo, G. Clerico et al., "Train delay prediction systems: a big data analytics perspective," Big data research, vol. 11, pp. 54–64, 2018.
[19] L. Oneto, E. Fumeo, and G. Clerico, "Advanced Analytics for Train Delay Prediction Systems by Including Exogenous Weather data," in Proceedings of the 2016 IEEE International Conference on Data Science and Advanced Analytics (DSAA), pp. 458–467, IEEE, Montreal, QC, Canada, October 2016.
[20] Q. Zhang, F. Chen, and T. Zhang, "Intelligent prediction and characteristic recognition for joint delay of high speed railway trains," Acta Automatica Sinica, vol. 45, no. 12, pp. 2251–2259, 2019.

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