1.被引论文：ELITE: An Intelligent Digital Twin-Based Hierarchical Routing Scheme for Softwarized Vehicular Networks

引用文献：

[1] Xiangyi Chen, Guangjie Han, Yuanguo Bi, Zimeng Yuan, Mahesh K. Marina, Yufei Liu, Hai Zhao, "Traffic Prediction-Assisted Federated Deep Reinforcement Learning for Service Migration in Digital Twins-Enabled MEC Networks", IEEE Journal on Selected Areas in Communications, vol.41, no.10, pp.3212-3229, 2023.

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allows idle infrastructure to be put into sleep mode post-migration, thereby reducing network operation cost. With the development of Artificial Intelligence (AI) and distributed learning technologies, a promising approach is to leverage Edge-AI and Federated Learning (FL) to establish a distributed learning architecture for intelligent service migration in MEC networks [7], [8], [9], [10].

Service migration based on Edge-AI necessitates a substantial volume of data for the construction of an effective model. Recently, the emerging Digital Twins (DT) technology has been instrumental in this aspect. DT can capture the status information of physical entities using sensor data, create corresponding virtual objects, and accumulate a vast amount of real data in the digital space [11], [12]. This data can be exploited for model training, state analysis, and risk assessment in AI-enabled networks. Therefore, distributed DT have been integrated into MEC networks, sinking real-time data processing to the edge plane [13]. It enables edge servers to leverage large volumes of data for Deep Learning (DL)-based model training, thereby supporting traffic prediction-assisted cost-efficient service migration in Digital Twin-enabled MEC (DT-MEC) networks.

proposed to tackle the imbalance of traffic data. Then, based on the predicted traffic demand, a Federated Cooperative cost-efficient Service Migration (FCSM) algorithm is proposed, which adaptively adjusts service migration strategies in response to the dynamic changes of the edge environment. To the best of our knowledge, this is the first paper that studies cost-efficient service migration considering future traffic demand in DT-MEC networks. Our contributions are four-fold as follows.

- Based on the analysis of real-world mobile traffic dataset, we propose a distributed traffic prediction approach that achieves efficient and low-cost mobile traffic prediction by integrating multi-order spatio-temporal information and edge model transfer.
- To achieve cost-efficient service migration, FCSM is proposed to enable online service migration in large-scale MEC networks, which facilitates multi-agent cooperative learning through intra-cluster parameter sharing and global asynchronous parameter aggregation.
- An analytical model is developed to demonstrate that the features extracted by MSTP contain multi-order spatio-temporal dependencies. Furthermore, the convergence of

参考文献：

impact on the parameters, we simplify the expression for the last term of the first inequality in (46). Substituting the result from (46) back into (45), we have

$$\|\boldsymbol{\theta}_k^{\tau_k} - \boldsymbol{\theta}^{\tau'}\| \leq GH\sqrt{N_k}\eta_k\delta \|\mathbf{W}\|. \tag{47}$$

Substituting the result from (47) successively back into (44) and (43), we have

$$\begin{aligned}&\mathbb{E}\left[J(\boldsymbol{\theta}^{\tau'}) - J(\boldsymbol{\theta}^{\tau-1})\right]\\&\leq \Upsilon\alpha GH\sqrt{N_k}\eta_k\delta^2\|\mathbf{W}\| + \frac{\beta}{2}\Upsilon^2\alpha^2G^2H^2N_k\eta_k^2\delta^2\|\mathbf{W}\|^2.\end{aligned} \tag{48}$$

According to (40), (42), and (48), we have

$$\begin{aligned}&\mathbb{E}\left[J\left(\boldsymbol{\theta}^{\tau}\right) - J\left(\boldsymbol{\theta}^{\tau-1}\right)\right]\\&\leq -\alpha\frac{\eta_k}{2N_k}\sum_{g=1}^{G}\sum_{j=1}^{N_k}\mathbb{E}\left[\left\|\nabla J\left(\boldsymbol{\theta}_{k,j}^{\tau',g}\right)\right\|^2\right]\\&\quad+\alpha\frac{\eta_k\sigma_{\max}^2GH}{2B}\frac{1+\zeta^2}{1-\zeta^2}\\&\quad+\Upsilon\alpha^2GH\sqrt{N_k}\eta_k\delta^2\|\mathbf{W}\|\\&\quad+\frac{\beta}{2}\Upsilon^2\alpha^3G^2H^2N_k\eta_k^2\delta^2\|\mathbf{W}\|^2.\end{aligned} \tag{49}$$

survey," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 869–904, 2nd Quart., 2020.

[8] D. C. Nguyen et al., "Enabling AI in future wireless networks: A data life cycle perspective," *IEEE Commun. Surveys Tuts.*, vol. 23, no. 1, pp. 553–595, 1st Quart., 2021.

[9] X. Chen, X. Wang, B. Yi, Q. He, and M. Huang, "Deep learning-based traffic prediction for energy efficiency optimization in software-defined networking," *IEEE Syst. J.*, vol. 15, no. 4, pp. 5583–5594, Dec. 2021.

[10] Q. Wu, X. Chen, Z. Zhou, L. Chen, and J. Zhang, "Deep reinforcement learning with spatio-temporal traffic forecasting for data-driven base station sleep control," *IEEE/ACM Trans. Netw.*, vol. 29, no. 2, pp. 935–948, Apr. 2021.

[11] R. Dong, C. She, W. Hardjawana, Y. Li, and B. Vucetic, "Deep learning for hybrid 5G services in mobile edge computing systems: Learn from a digital twin," *IEEE Trans. Wireless Commun.*, vol. 18, no. 10, pp. 4692–4707, Oct. 2019.

[12] L. Zhao, Z. Bi, A. Hawbani, K. Yu, Y. Zhang, and M. Guizani, "ELITE: An intelligent digital twin-based hierarchical routing scheme for softwarized vehicular networks," *IEEE Trans. Mobile Comput.*, vol. 22, no. 9, pp. 5231–5247, Sep. 2023, doi: 10.1109/TMC.2022.3179254.

[13] federated learning and blockchain for edge association in digital twin empowered 6G networks," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 5098–5107, Jul. 2021.

[14] A. Furno, M. Fiore, R. Stanica, C. Ziemlicki, and Z. Smoreda, "A tale of ten cities: Characterizing signatures of mobile traffic in urban areas," *IEEE Trans. Mobile Comput.*, vol. 16, no. 10, pp. 2682–2696, Oct. 2017.

[15] D. Naboulsi, M. Fiore, S. Ribot, and R. Stanica, "Large-scale mobile traffic analysis: A survey," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 124–161, 1st Quart., 2016.

[16] F. Xu et al., "Big data driven mobile traffic understanding and forecasting: A time series approach," *IEEE Trans. Serv. Comput.*, vol. 9, no. 5, pp. 796–805, Sep. 2016.

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[2] Hansong Xu, Jun Wu, Qianqian Pan, Xinping Guan, Mohsen Guizani, "A Survey on Digital Twin for Industrial Internet of Things: Applications, Technologies and Tools", IEEE Communications Surveys & Tutorials, vol.25, no.4, pp.2569-2598, 2023.

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引用部分：

in the digital twin. To enable the predictive maintenance, Aivaliotis et al. in [93] proposed the digital twin-based remaining useful life prediction for manufacturing machinery, similar to the digital twin-driven predictive maintenance of CNC machine tool, proposed by Luo et al. in [94].

As seen in Table III, there are more research papers focused on the design, implementation, and testing phases than on the situation awareness and predictive maintenance phases. The main reason is that predictive maintenance requires the accuracy of machine learning predictive models, which relies heavily on models and data. However, current digital twin models are coarse-grained and industrial data are not sufficiently accessible. In addition, situational awareness requires a near-instant and high-throughput communication network for synchronization between the physical system and the digital twin, such as 6G, which is not currently available. There are significantly more applications in industry than in other application areas, such as transportation and energy. This is due to the fourth industrial revolution, also known as Industry 4.0, where the integration of IoT technologies into industry has been a trending research topic for many years. However, we can foresee that the digital twin can further accelerate the development of industry, transportation, and energy by integrating intelligent decision making and safe operation solutions [116], [117], [118].

D. Lessons Learned in DT-IIoT Overview

We summarize the key digital twin features from an economic, intelligence, and security perspective, as shown in the figure 8.

transmit control signals and commands back to the intelligent IIoT system. System operation data is massive, including system parameters, operation states, models of communication networks, computing platforms, control loops, and physical processes in both the network and physical domains. However, current communication networks, such as 4G and 5G, cannot meet the performance requirements of digital twin synchronization, which requires research on 6G.

- *Efficient resource allocation and scheduling solutions:* AI algorithms, such as predictive models based on deep neural networks, require a large number of computational resources for training. A centralized cloud computing architecture has sufficient computational resources, but it also exposes inherent poor latency performance. Therefore, hybrid cloud-edge computing architectures leverage computational resources at the edge to reduce communication latency. In addition, the problem of joint resource management and scheduling becomes increasingly complex considering highly integrated control, communication, and computation.

To meet the above requirements, AI algorithms in digital twins have great potential to enable intelligent analysis and decision-making. AI algorithms have been used for the prediction, classification, and automation of many consumer applications, such as natural language processing, computer vision, etc., which pave the way for the adoption of AI algorithms in digital twins. Therefore, we investigate preliminary work on intelligent solutions for digital twins in Section III.

参考文献：

ledger technologies: Application of predictive maintenance," in *Proc. 27th Telecommun. Forum (TELFOR)*, 2019, pp. 1–4.

[116] L. Zhao, Z. Bi, A. Hawbani, K. Yu, Y. Zhang, and M. Guizani, "ELITE: An intelligent digital twin-based hierarchical routing scheme for softwarized vehicular networks," *IEEE Trans. Mobile Comput.*, early access, May 31, 2022, doi: 10.1109/TMC.2022.3179254.

[117] Z. Zhou et al., "Secure and latency-aware digital twin assisted resource scheduling for 5G edge computing-empowered distribution grids," *IEEE Trans. Ind. Informat.*, vol. 18, no. 7, pp. 4933–4943, Jul. 2022.

[118] Y. Tai et al., "Digital twin-enabled IoMT system for surgical simulation using rAC-GAN," *IEEE Internet Things J.*, vol. 9, no. 21, pp. 20918–20931, Nov. 2022.

[119] M. V. Shcherbakov, A. V. Glotov, and S. V. Cheremisinov, "Proactive and predictive maintenance of cyber-physical systems," in *Cyber-Physical Systems: Advances in Design & Modelling*. Cham, Switzerland: Springer, 2020, pp. 263–278.

[120] Z. Qu et al., "Power cyber-physical system risk area prediction using dependent Markov chain and improved grey wolf optimization," *IEEE Access*, vol. 8, pp. 82844–82854, 2020.

[121] J. Lee, S. D. Noh, H.-J. Kim, and Y.-S. Kang, "Implementation of cyber-physical production systems for quality prediction and operation control in metal casting," *Sensors*, vol. 18, no. 5, p. 1428, 2018.

[122] M. Lermer and C. Reich, "Creation of digital twins by combining fuzzy rules with artificial neural networks," in *Proc. IEEE 45th Annu. Conf. Ind. Electron. Soc. (IECON)*, vol. 1, 2019, pp. 5849–5854.

[123] M. D. Anis, S. Taghipour, and C.-G. Lee, "Optimal RUL estimation: A state-of-art digital twin application," in *Proc. IEEE Annu. Rel. Maintain. Symp. (RAMS)*, 2020, pp. 1–7.

K. Kok, "Machine learning for digital twins to predict responsiveness of cyber-physical energy systems," in *Proc. 8th Workshop Model. Simulat. Cyber Phys. Energy Syst.*, 2020, pp. 1–6.

[139] X. Xie, A. K. Parlikad, and R. S. Puri, "A neural ordinary differential equations based approach for demand forecasting within power grid digital twins," in *Proc. IEEE Int. Conf. Commun. Control Comput. Technol. Smart Grids (SmartGridComm)*, 2019, pp. 1–6.

[140] H. Wang, Y. Wu, G. Min, and W. Miao, "A graph neural network-based digital twin for network slicing management," *IEEE Trans. Ind. Informat.*, vol. 18, no. 2, pp. 1367–1376, Feb. 2022.

[141] J. M. Taylor and H. R. Sharif, "Leveraging digital twins to enhance performance of IoT in disadvantaged networks," in *Proc. IEEE Int. Wireless Commun. Mobile Comput. (IWCMC)*, 2020, pp. 1303–1308.

[142] G. Szabó, J. Pető, L. Németh, and A. Vidács, "Information gain regulation in reinforcement learning with the digital twins' level of realism," in *Proc. IEEE 31st Annu. Int. Symp. Pers. Indoor Mobile Radio Commun.*, 2020, pp. 1–7.

[143] Y. Dai, K. Zhang, S. Maharjan, and Y. Zhang, "Deep reinforcement learning for stochastic computation offloading in digital twin networks," *IEEE Trans. Ind. Informat.*, vol. 17, no. 7, pp. 4968–4977, Jul. 2021.

[144] S. Cui, D. Wang, J. Li, and M. Zhang, "Dynamic programmable optical transceiver configuration based on digital twin," *IEEE Commun. Lett.*, vol. 25, no. 1, pp. 205–208, Jan. 2021.

[145] D. An, Q. Yang, W. Yu, D. Li, and W. Zhao, "LoPrO: Location privacy-preserving online auction scheme for electric vehicles joint bidding and charging," *Future Gener. Comput. Syst.*, vol. 107, pp. 394–407, Jun. 2020.

[3] Maram Bani Younes, Azzedine Boukerche, "A Novel Traffic Characteristics Aware and Context Prediction Protocol for Intelligent Connected Vehicles", IEEE Transactions on Vehicular Technology, vol.72, no.8, pp.9897-9908, 2023.

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scenario's physical and traffic context based on the analyzed traffic data. This protocol helps to predict the context of the investigated area of interest in terms of existing entrance/exit points, intersections, roundabouts, U-turns, etc. Moreover, ad-hoc contexts such as highly congested areas and accidents on the road networks. Thus, it helps to determine the contents of the area of interest, which verify the notification of the digital map and replaces the broken or absent ones. This protocol has been tested over highway and downtown road scenarios. Downtown roads' physical context is richer than highway scenarios' context.

The remainder of this article is organized as follows: Section II investigated previous studies that analyzed and utilized the traffic characteristics over road networks. Section III illustrates the physical context of downtown and highway road scenarios. Section IV introduces the special traffic contexts over the road network that are considered in this work. It investigates their characteristics and effects over several downtown and highway road scenarios. Section V presents the details of the sequential phases in the proposed protocol. Section VI evaluates the performance of the proposed protocol over highway and downtown scenarios. Finally, Section VII draws the conclusion of the entire paper.

schools, gas stations, theaters, hospitals, or malls. These roads witness higher traffic densities during certain periods of time. Several studies have investigated the effects of the existence of these destinations on the traffic distribution over the surrounding road segments [21], [22]. Santamaria et al. [19], co2 have proposed a re-routing algorithm for CO_2 emissions reduction using distributed predictive congestion aware principles. Advanced technologies such as the digital twin-based hierarchical routing scheme [40], temporal graph routing algorithm [41], and online sequential learning-based adaptive routing [42] have been used to predict the most efficient path over the road networks.

On the other hand, several research studies have been proposed to control the road intersections at the downtown areas [14], [23], [24]. Each road intersection is shared among several traffic flows, advanced mechanisms are required to schedule the competing traffic flows there. Driving rules, stop signs, roundabouts, and traffic lights are proposed to control the traffic at road intersections. Neetesh et al. [23], density investigated the traffic density of the input flows at each signalized intersection to efficiently set the phases of the located traffic light. The length of the queue lines for the competing traffic flows is investigated as the main parameter to set the phases of the traffic light

参考文献：

flow prediction," in *Proc. 19th ACM Int. Symp. Mobility Manage. Wireless Access*, 2021, pp. 71–76.

[36] S. Tsanakas, A. Hameed, J. Violos, and A. Leivadeas, "An innovative neuro-genetic algorithm and geometric loss function for mobility prediction," in *Proc. 19th ACM Int. Symp. Mobility Manage. Wireless Access*, 2021, pp. 25–32.

[37] R. Qaddoura, M. Bani Younes, and A. Boukerche, "Predicting traffic characteristics of real road scenarios in Jordan and gulf region," in *Proc. 17th ACM Symp. QoS Secur. Wireless Mobile Netw.*, 2021, pp. 115–121.

[38] B. Häfner, J. Jiru, H. Schepker, G. A. Schmitt, and J. Ott, "Preventing failures of cooperative maneuvers among connected and automated vehicles," in *Proc. 24th Int. ACM Conf. Model., Anal., Simul. Wireless Mobile Syst.*, 2021, pp. 5–12.

[39] C. Ayimba, M. Segata, P. Casari, and V. Mancuso, "Closer than close: Mec-assisted platooning with intelligent controller migration," in *Proc. 24th Int. ACM Conf. Model. Anal. Simul. Wireless Mobile Syst.*, 2021, pp. 27–32.

[40] L. Zhao, Z. Bi, A. Hawbani, K. Yu, Y. Zhang, and M. Guizani, "ELITE: An intelligent digital twin-based hierarchical routing scheme for softwarized vehicular networks," *IEEE Trans. Mobile Comput.*, vol. 22, no. 9, pp. 5231–5247, Sep. 2023.

[41] L. Zhao et al., "A novel prediction-based temporal graph routing algorithm for software-defined vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 13275–13290, Aug. 2022.

[42] L. Zhao et al., "Novel online sequential learning-based adaptive routing for edge software-defined vehicular networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 5, pp. 2991–3004, May 2020.

[43] Y. Zhang, K. Gao, Y. Zhang, and R. Su, "Traffic light scheduling for pedestrian-vehicle mixed-flow networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 4, pp. 1468–1483, Apr. 2019.

[44] Y. Zhang, Y. Zhang, and R. Su, "Pedestrian-safety-aware traffic light control strategy for urban traffic congestion alleviation," *IEEE Trans. Intell. Transp. Syst.* vol. 22, no. 1, pp. 178–193, Jan. 2021.

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[4] Zhiwei Guo, Keping Yu, Kostromitin Konstantin, Shahid Mumtaz, Wei Wei, Peng Shi, Joel J. P. C. Rodrigues, "Deep Collaborative Intelligence-Driven Traffic Forecasting in Green Internet of Vehicles", IEEE Transactions on Green Communications and Networking, vol.7, no.2, pp.1023-1035, 2023.

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and graph embedding together and proposes a deep collaborative intelligence-driven traffic forecasting model in GIoV. By establishing more reliable feature spaces for traffic flow prediction, forecasting efficiency is expected to be promoted. Specifically, deep embedding is utilized to generate more abstract representation for basic features of road networks, and graph embedding is employed to update feature representation for different times-

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I. Introduction

With the continuous development of Vehicular networks and green communication [1], green Internet of Vehicles (GIoV) has received great progress during past few years [2]. The Green Vehicle Internet (IoV) is a sustainable vehicle communication and networking. It is a special mobile ad-hoc network [3]. Future green IoV systems are expected to be hierarchically integrated with the distributed edge computing components and the remote centralized computing server [4], [5]. By providing reliable and stable electricity access, GIoV can not only facilitate continuity of vehicle driving, but also support massive vehicular interconnection [6]. In this context, the road networks under GIoV are going to become a kind of key infrastructures in smart cities [7]. The GIoV strengthens the relationship among roads, vehicles and users by combining technologies of vehicular communication and computational intelligence [8], [9]. As a result, a set of convenient and efficient road transportation service systems can be formed. Reasonable management scheduling is the way to ensure normal operations of GIoV [10]. To achieve this goal, accurate prediction of traffic flow in GIoV has become an important demand to be investigated [11]. In recent years, the use of computational intelligence in traffic flow forecasting has become the mainstream idea to solve this problem [12]. Computational intelligence aims to explore how to make computers realize self-learning and improvement like human beings [13]. It is widely used in data mining tasks of network streams, such as social networks [14]. Expectedly, the machine learning algorithms can also be well applied to traffic forecasting in GIoV [15].

参考文献：

References

[1] C. Wu, Z. Liu, F. Liu, T. Yoshinaga, Y. Ji, and J. Li, "Collaborative learning of communication routes in edge-enabled multi-access vehicular environment," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 4, pp. 1155–1165, Dec. 2020.

[2] X. Liu, X. B. Zhai, W. Lu, and C. Wu, "QoS-guarantee resource allocation for multibeam satellite industrial Internet of Things with NOMA," *IEEE Trans. Ind. Informat.*, vol. 17, no. 3, pp. 2052–2061, Mar. 2021.

[3] J. Wang, K. Zhu, and E. Hossain, "Green Internet of Vehicles (IoV) in the 6G era: Toward sustainable vehicular communications and networking," *IEEE Trans. Green Commun. Netw.*, vol. 6, no. 1, pp. 391–423, Mar. 2022.

[4] L. Zhao, Z. Bi, A. Hawbani, K. Yu, Y. Zhang, and M. Guizani, "ELITE: An intelligent digital twin-based hierarchical routing scheme for softwarized vehicular networks," *IEEE Trans. Mobile Comput.*, early access, May 31, 2022, doi: 10.1109/TMC.2022.3179254.

[5] D. Meng *et al.*, "A data-driven intelligent planning model for UAVs routing networks in mobile Internet of Things," *Comput. Commun.*, vol. 179, pp. 231–241, Nov. 2021.

[6] R. Yin, Z. Wu, S. Liu, C. Wu, J. Yuan, and X. Chen, "Decentralized radio resource adaptation in D2D-U networks," *IEEE Internet Things J.*, vol. 8, no. 8, pp. 6720–6732, Apr. 2021.

[7] L. Zhao, H. Chai, Y. Han, K. Yu, and S. Mumtaz, "A collaborative V2X data correction method for road safety," *IEEE Trans. Rel.*, vol. 71, no. 2, pp. 951–962, Jun. 2022.

[23] H. Qiu, Q. Zheng, M. Msahli, G. Memmi, M. Qiu, and J. Lu, "Topological graph convolutional network-based urban traffic flow and density prediction," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 4560–4569, Jul. 2021.

[24] X. Chen *et al.*, "TSSRGCN: Temporal spectral spatial retrieval graph convolutional network for traffic flow forecasting," in *Proc. 20th IEEE Int. Conf. Data Min. (ICDM)*, Sorrento, Italy, Nov. 2020, pp. 954–959.

[25] X. Zhang, C. Huang, Y. Xu, and L. Xia, "Spatial-temporal convolutional graph attention networks for citywide traffic flow forecasting," in *Proc. 29th ACM Int. Conf. Inf. Knowl. Manag.*, Oct. 2020, pp. 1853–1862.

[26] M. Li and Z. Zhu, "Spatial-temporal fusion graph neural networks for traffic flow forecasting," in *Proc. 25th AAAI Conf. Artif. Intell. (AAAI)*, Feb. 2021, pp. 4189–4196. [Online]. Available: https://ojs.aaai.org/index.php/AAAI/article/view/16542

[27] Z. Cui, K. Henrickson, R. Ke, and Y. Wang, "Traffic graph convolutional recurrent neural network: A deep learning framework for network-scale traffic learning and forecasting," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 11, pp. 4883–4894, Nov. 2020.

[28] H. Peng *et al.*, "Spatial temporal incidence dynamic graph neural networks for traffic flow forecasting," *Inf. Sci.*, vol. 521, pp. 277–290, Jun. 2020.

[29] F. Zhou, Q. Yang, K. Zhang, G. Trajcevski, T. Zhong, and A. A. Khokhar, "Reinforced spatiotemporal attentive graph neural networks for traffic forecasting," *IEEE Internet Things J.*, vol. 7, no. 7, pp. 6414–6428, Jul. 2020.

[30] C. Zheng, X. Fan, C. Wang, and J. Qi, "GMAN: A graph multi-attention network for traffic prediction," in *Proc. 44th AAAI Conf. Artif. Intell.*

2. 被引论文： A Novel Generation Adversarial Network-based Vehicle Trajectory Prediction Method for Intelligent Vehicular Networks

引用文献：

[1] Feng-Jie Li, Chun-Yang Zhang, C. L. Philip Chen, "STS-DGNN: Vehicle Trajectory Prediction via Dynamic Graph Neural Network With Spatial–Temporal Synchronization", IEEE Transactions on Instrumentation and Measurement, vol.72, pp.1-13, 2023.

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in a one-stage framework rather than independently modeling the spatial relationship and temporal correlations of vehicles in two-stage models. The proposed model also considers the dynamic nature of graph sequence by utilizing gate recurrent unit (GRU) to update the graph neural network (GNN) parameters dynamically. The spatial–temporal features are subsequently conveyed to convolutional neural networks (CNNs) and processed by a multilayer perceptron (MLP) to generate the ultimate trajectories. Finally, to illustrate the effectiveness of the STS-DGNN model, the model is assessed on three well-known datasets, namely highD, EWAP, and UCY. The results confirm that our model performs better at making predictions than cutting-edge models. The visualization results intuitively explain that our method can extract sophisticated and subtle multivehicle interactions, resulting in accurate predictions.

***Index Terms*— Autonomous driving, dynamic graph, graph neural network (GNN), spatial–temporal dependencies, vehicle trajectory prediction.**

I. Introduction

IN RECENT years, with the rapid developments of technologies in autonomous driving, autonomous vehicles are

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Vehicle trajectory prediction is a challenging task in practice due to the intricate dynamics of driving scenarios and complex spatial–temporal dependencies of vehicle trajectories. Early works usually predict vehicle trajectories in a noninteraction way, such as physics-based models [2], maneuver-based models [3], or combinations of the two [4], [5]. Besides, some RNN-based techniques, such as gate recurrent unit (GRU) and long short term memory (LSTM), have been implemented for identical tasks. However, these methods neglect the interactions between vehicles and can only achieve short-term predictions. Many existing works have confirmed that modeling intervehicle interactions is essential to enhance trajectory prediction accuracy in highly dynamic interaction driving scenarios. As a result, the above approaches were quickly substituted by interaction methods that considered the mutual influences among vehicles. More recently, methods based on attention mechanisms [6], [7], [8], [9] have been widely used for modeling intervehicle interactions. The incorporation of the attention mechanism has been proven to effectively mitigate the impact of extraneous information and amplify the influence of pertinent information, thereby leading to the superior predictive performance of the attention-based models compared to the methodologies that overlook intervehicle interactions. Currently, numerous powerful methods, such as graph neural network (GNN) and its variants [10], [11], [12], [13], [14], [15], have attracted much attention for their ability to model traffic scenes well. Pareja et al. [12] develop an approach called EvolveGCN, which integrates LSTMs and GRUs with graph convolutional networks (GCNs) to deal with dynamic graphs. Moreover, various other approaches [16], [17], [18], [19], [20], [21], [22], [23], [24], [25] have also been proposed for trajectory prediction tasks.

参考文献：

further improves the prediction accuracy of the model. In particular, to the extent of our knowledge, this research represents the first-ever attempt to jointly extract the spatial–temporal features among cars. The performance of the STS-DGNN model was assessed on the highD, EWAP and UCY datasets and compared with other existing models. The outcomes illustrate that the proposed model has the best prediction performance. Simultaneously, several ablation studies are conducted to ascertain the efficacy of each module incorporated within our proposed model. Moreover, we also implement qualitative analyses of the influence of adjacent vehicles on trajectory prediction under different traffic scenes. The visualization results evidently depict that the STS-DGNN model has the ability to comprehend intricate and subtle interactions among multiple vehicles and can produce reasonable predictions concerning these interactions.

Currently, STS-DGNN can only produce deterministic predictions, whereas the motion of the vehicles is intrinsically multimodal. In future work, we would like to add other road users and their interactions, such as bicycles, pedestrians, buses, etc., to our model to improve prediction accuracy. In addition, we will explore methods to enhance the generalizability of the proposed model across different driving environments.

[12] A. Pareja, "Evolvegcn: Evolving graph convolutional networks for dynamic graphs," in *Proc. AAAI Conf. Artif. Intell.*, 2020, vol. 34, no. 4, pp. 5363–5370.

[13] J. Li, H. Ma, Z. Zhang, J. Li, and M. Tomizuka, "Spatio-temporal graph dual-attention network for multi-agent prediction and tracking," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 10556–10569, Aug. 2022.

[14] X. Chen, H. Zhang, F. Zhao, Y. Hu, C. Tan, and J. Yang, "Intention-aware vehicle trajectory prediction based on spatial–temporal dynamic attention network for Internet of Vehicles," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 19471–19483, Oct. 2022.

[15] L. Ye, Z. Wang, X. Chen, J. Wang, K. Wu, and K. Lu, "GSAN: Graph self-attention network for learning spatial–temporal interaction representation in autonomous driving," *IEEE Internet Things J.*, vol. 9, no. 12, pp. 9190–9204, Jun. 2022.

[16] X. Mo, Y. Xing, and C. Lv, "Graph and recurrent neural network-based vehicle trajectory prediction for highway driving," in *Proc. IEEE Int. Intell. Transp. Syst. Conf. (ITSC)*, Sep. 2021, pp. 1934–1939.

[17] R. Chandra et al., "Forecasting trajectory and behavior of road-agents using spectral clustering in graph-LSTMs," *IEEE Robot. Autom. Lett.*, vol. 5, no. 3, pp. 4882–4890, Jul. 2020.

[18] L. Zhao, Y. Liu, A. Y. Al-Dubai, A. Y. Zomaya, G. Min, and A. Hawbani, "A novel generation-adversarial-network-based vehicle trajectory prediction method for intelligent vehicular networks," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 2066–2077, Feb. 2021.

[19] S. Kim, D. Kum, and J. W. Choi, "RECUP Net: Recursive prediction network for surrounding vehicle trajectory prediction with future trajectory feedback," in *Proc. IEEE 23rd Int. Conf. Intell. Transp. Syst. (ITSC)*, Sep. 2020, pp. 1–6.

[20] Z. Zhong, Y. Luo, and W. Liang, "STGM: Vehicle trajectory prediction based on generative model for spatial–temporal features," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 10, pp. 18785–18793, Oct. 2022.

[2] Qingyu Meng, Hongyan Guo, Yanran Liu, Hong Chen, Dongpu Cao, "Trajectory Prediction for Automated Vehicles on Roads With Lanes Partially Covered by Ice or Snow", IEEE Transactions on Vehicular Technology, vol.72, no.6, pp.6972-6986, 2023.

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a GNN enables information exchange between nodes, a graph query mechanism that integrates local graph information and guides prediction results based on the local states of the nearest observable nodes is proposed. In addition, a multihead attention mechanism projects neighboring states to the graph, describing interactions between vehicles and the state of the traffic flow, and a two-layer graph attention network (GAT) enables information aggregation and describes node correlations. Experiments on the nuScenes dataset show that our prediction method outperforms state-of-the-art prediction systems, including Traj++, SG-NET, and P2T, when lane lines are occluded. Vehicle trajectories on roads covered by ice and snow can be accurately predicted based on observable information.

***Index Terms*—Graph attention, gate recurrent unit, graph neural network, icy and snowy environment, vehicle trajectory prediction.**

I. Introduction

WITH advancements in artificial intelligence, the safety and efficiency of intelligent vehicles in challenging working conditions have begun to improve [1]. However,

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Recent research on neighbor vehicle trajectory prediction has achieved significant results with the successful application of recurrent neural networks (RNNs) [3], [4]. The traditional long short-term memory (LSTM) network encoder-decoder structure serves as the foundation for organizing trajectory sequences and makes predictions by fitting nonlinear models of time variables [5]. The gated recurrent unit (GRU) achieves encoding and prediction effects similar to the LSTM model with fewer parameters and has become increasingly popular [6]. On this basis, the introduction of temporal and spatial attention mechanisms improves the prediction accuracy and interpretability of the model [7]. In addition, the multihead strategy proposed by Google in the fully self-attention-based transformer can fully capture the detailed features of the input sequence subspace and has achieved extensive research in vehicle trajectory prediction [8]. In contrast to multimodal trajectories, generative models based on generative adversarial networks (GANs) and variational autoencoders (VAEs) have been extensively studied [9]. In recent years, these models have used the context constraints of high-definition (HD) maps to improve their prediction accuracy and stability. The advantages of convolutional neural networks (CNNs) for extracting detailed texture features have been fully described, and map information has been realized [10]. In recent years, graph neural networks (GNNs) have been successfully applied in trajectory prediction because they can represent topological structures when presented with structured data [11]. However, these prediction schemes are based on idealized road structures, with relatively clean data that cover only conventional working conditions.

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and the limitations of the map. For example, the acceleration of vehicles are crucial in traffic light intersections, and predictions in roundabouts depend on the vehicle yaw angle information. The method proposed in this article combines multimodal vehicle historical state encoding to extract map features at a deeper level, providing the optimal prediction results from multiple perspectives.

VI. Conclusion

In this article, the ability of a graph neural network (GNN) to aggregate the information of surrounding nodes was utilized to develop a method for predicting the trajectories of neighboring vehicles when lane lines are covered by ice and snow. In cases with unobservable lane lines, a graph query mechanism was used to integrate the local graph of the target vehicle and collect the nearest available nodes to infer driving trajectories. To represent vehicle interactions, a crucial factor that impacts the prediction results, a multihead attention mechanism was used to project the surrounding vehicle states to the graph, thus combining the vehicle and node features. Graph aggregation was achieved through a graph attention network (GAT), which quantitatively described the transfer relationship between adjacent nodes while reasonably constraining the dynamic trajectory of the vehicle. The experiment used the nuScenes dataset and introduced ice and snow occlusions, and the error convergence during the training process was smooth. Compared with state-of-the-art prediction methods such as Traj++, SG-NET, and P2T, our model has clear performance advantages in ice and snow environments, outperforming existing models on three critical indicators, including the minimum average displacement error (MinADE), minimum final displacement error (MinFDE), and miss rate (MR).

[5] S. H. Park, B. Kim, C. M. Kang, C. C. Chung, and J. W. Choi, "Sequence-to-sequence prediction of vehicle trajectory via LSTM encoder-decoder architecture," in *Proc. IEEE Intell. Veh. Symp.*, 2018, pp. 1672–1678.

[6] Y. Zhi, Z. Bao, S. Zhang, and R. He, "BiGRU based online multi-modal driving maneuvers and trajectory prediction," *Proc. Inst. Mech. Eng. Part D-J. Automobile Eng.*, vol. 235, no. 14, pp. 3431–3441, Apr. 2021.

[7] H. Guo, Q. Meng, D. Cao, H. Chen, J. Liu, and B. Shang, "Vehicle trajectory prediction method coupled with ego vehicle motion trend under dual attention mechanism," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–16, 2022.

[8] H. Kim, D. Kim, G. Kim, J. Cho, and K. Huh, "Multi-head attention based probabilistic vehicle trajectory prediction," in *Proc. IEEE Intell. Veh. Symp.*, 2020, pp. 1720–1725.

[9] L. Zhao, Y. Liu, A. Y. Al-Dubai, A. Y. Zomaya, G. Min, and A. Hawbani, "A novel generation-adversarial-network-based vehicle trajectory prediction method for intelligent vehicular networks," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 2066–2077, Feb. 2021.

[10] K. Messaoud, N. Deo, M. M. Trivedi, and F. Nashashibi, "Trajectory prediction for autonomous driving based on multi-head attention with joint agent-map representation," in *Proc. IEEE Intell. Veh. Symp.*, 2021, pp. 165–170.

[11] Z. Li, J. Gong, C. Lu, and Y. Yi, "Interactive behavior prediction for heterogeneous traffic participants in the urban road: A graph-neural-network-based multitask learning framework," *IEEE-ASME Trans. Mechatron.*, vol. 26, no. 3, pp. 1339–1349, Jun. 2021.

[12] N. Mutoh, "Driving and braking torque distribution methods for front-and rear-wheel-independent drive-type electric vehicles on roads with low friction coefficient," *IEEE Trans. Ind. Electron.*, vol. 59, no. 10, pp. 3919–3933, Oct. 2012.

[13] G. Neel and S. Saripalli, "Improving bounds on occluded vehicle states for use in safe motion planning," in *Proc. IEEE Int. Symp. Saf., Secur., Rescue Robot.*, 2020, pp. 268–275.

[14] S. Tuteja, S. Poddar, D. Agrawal, and V. Karar, "PredictV: A vehicle prediction scheme to circumvent occluded frames," *IEEE Access*, vol. 10, pp. 20029–20042, 2022.

[15] Y. Zhang, Z. Lu, D. Ma, J.-H. Xue, and Q. Liao, "Ripple-GAN: Lane line detection with ripple lane line detection network and wasserstein GAN," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 3, pp. 1532–1542, Mar. 2021.

[16] Y. Xing, C. Lv, and D. Cao, "Personalized vehicle trajectory prediction based on joint time-series modeling for connected vehicles," *IEEE Trans. Veh. Technol.*, vol. 69, no. 2, pp. 1341–1352, Feb. 2020.

[17] Y. Cai et al., "Environment-attention network for vehicle trajectory prediction," *IEEE Trans. Veh. Technol.*, vol. 70, no. 11, pp. 11216–11227, Nov. 2021.

[3] Bingyi Liu, Yang Sheng, Xun Shao, Yusheng Ji, Weizhen Han, Enshu Wang, Shengwu Xiong, "Collaborative Intelligence Enabled Routing in Green IoV: A Grid and Vehicle Density Prediction-Based Protocol", IEEE Transactions on Green Communications and Networking, vol.7, no.2, pp.1012-1022, 2023.

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引用部分：

decision-making for route selection. However, since urban traffic has unique characteristics such as complex traffic conditions and frequent communication link disconnections, only position information cannot completely reflect communication states among vehicles. Some protocols select vehicles to build a routing path before sending the packets [16], [17]. However, due to the uneven distribution and high mobility of vehicles, a routing path consisting of a series of vehicles is unreliable in a VCPS environment. With the development of distributed and collaborative intelligence in VCPS, several protocols have proposed message forwarding approaches based on the direction and position prediction of each vehicle [18], [19]. However, position prediction for each vehicle in an urban scene brings enormous computation and time cost, making it difficult to be applied in a large-scale VCPS. In addition to the above challenges, due to the lack of overall understanding of the global network topology, routing covering a large area in a modern city always leads to high calculation and implementation complexity.

Benefiting from the huge amount of data from onboard sensors and collaborative intelligence-enabled IoV, a vehicle density prediction-based routing protocol named VDPGrid is proposed in this paper. In particular, collaborative routing decision-making is implemented inside the IoV by sharing data and computation resources among vehicles instead of sending all the data to a centralized cloud server. To this end, we divide the map into a series of grids so that the packets can be forwarded between different grids rather than across the entire city map. In this way, both communication over-

density prediction model. Section IV introduces a grid-based communication model and formulates a routing path weight evaluation scheme. The VDPGrid communication scheme is discussed in Section V and the performance of the method is evaluated in Section VI. Finally, we conclude this paper in Section VII.

II. Related Work

This section discusses the related work in terms of trajectory prediction and grid-based communication methods.

A. Trajectory Prediction Based on Neural Network Models

Trajectory prediction is one of the key issues in traffic control and guidance systems [20], [21]. For a given prediction-based routing protocol, its performance improves as prediction accuracy improves. Therefore, it is significant to find the most suitable model for trajectory prediction. Similar to voice data and natural language data, trajectory data is also time-related data [22]. In recent years, some existing studies have applied neural network models for trajectory data mining. Xu *et al.* [23] used LSTM [24] to learn the time series characteristics of taxi demand data. Cui *et al.* [25] used LSTM to predict vehicle trajectories in multiple steps. Compared with the Hidden Markov Model, the experimental results show that LSTM can model vehicle trajectory prediction more accurately. Wu *et al.* [26] input the first few points in the trajectory

参考文献：

[22] L. Zhao, Y. Liu, A. Al-Dubai, A. Y. Zomaya, G. Min, and A. Hawbani, "A novel generation adversarial network-based vehicle trajectory prediction method for intelligent vehicular networks," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 2066–2077, Feb. 2021.

[23] J. Xu, R. Rahmatizadeh, L. Bölöni, and D. Turgut, "Real-time prediction of taxi demand using recurrent neural networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 8, pp. 2572–2581, Aug. 2018.

[24] D. Xu *et al.*, "Tensorized LSTM with adaptive shared memory for learning trends in multivariate time series," in *Proc. AAAI Conf. Artif. Intell.*, vol. 34, 2020, pp. 1395–1402.

[25] J. Cui, X. Zhou, Y. Zhu, and Y. Shen, "A road-aware neural network for multi-step vehicle trajectory prediction," in *Proc. Int. Conf. Database Syst. Adv. Appl.*, 2018, pp. 701–716.

[26] F. Wu, K. Fu, Y. Wang, Z. Xiao, and X. Fu, "A spatial-temporal-semantic neural network algorithm for location prediction on moving objects," *Algorithms*, vol. 10, no. 2, p. 37, 2017.

[27] D. Wang, J. Zhang, W. Cao, J. Li, and Y. Zheng, "When will you arrive? Estimating travel time based on deep neural networks," in *Proc. AAAI Conf. Artif. Intell.*, vol. 32, 2018, pp. 2500–2507.

[28] J. Lv, Q. Li, Q. Sun, and X. Wang, "T-CONV: A convolutional neural network for multi-scale taxi trajectory prediction," in *Proc. IEEE Int. Conf. Big Data Smart Comput. (Bigcomp)*, 2018, pp. 82–89.

[29] B. Kim, C. M. Kang, J. Kim, S. H. Lee, C. C. Chung, and J. W. Choi,

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[4] Ryan Wen Liu, Maohan Liang, Jiangtian Nie, Wei Yang Bryan Lim, Yang Zhang, Mohsen Guizani, "Deep Learning-Powered Vessel Trajectory Prediction for Improving Smart Traffic Services in Maritime Internet of Things", IEEE Transactions on Network Science and Engineering, vol.9, no.5, pp.3080-3094, 2022.

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attracted significant attention in vehicle trajectory prediction and traffic situation estimation. Note that trajectory prediction can be regarded as a time-series classification or generation problem. The RNN [9], [50] and its extensions have become the most representative prediction methods. For example, the naïve LSTM [10], social LSTM [51], deep convolutional LSTM [52], social graph convolutional LSTM [53], and states refinement LSTM [54], have been proposed to guarantee prediction accuracy and robustness. The main motivation is that LSTM performs well in learning the long-term dependency relationships between timestamped points in trajectories of interest. In [55], a two-stage prediction framework, i.e., trajectory proposal network (TPNet), was suggested to generate more natural prediction under physical constraints. Motivated by the success of TPNet, a multi-stage LSTM framework was suggest to predict the future location of a vessel with higher accuracy [19]. In addition, the generative adversarial network (GAN) has been exploited in trajectory prediction applications [56]. Both LSTM and GAN were jointly employed to deal with trajectory prediction with better generalizability [57]. Inspired by generative models, a dual linear auto-encoder method has been presented to predict entire vessel trajectories [58].

The location of a timestamped point P in collected AIS data is conventionally represented by the geographic coordinate system, including both longitude and latitude coordinates. For the sake of computation, we introduce the Mercator projection [14] to convert the geographic coordinates to the Cartesian coordinates for all timestamped points in AIS-based vessel trajectories.

A vessel trajectory is essentially an ordered series of timestamped points, as presented in Definition 3.2.

Definition 3.2: Vessel Trajectory: A vessel trajectory $\mathcal{T}$ is commonly represented in the form of a series of timestamped points $P^{N_1 \le N_t \le N_p}$ recorded by AIS devices, i.e., $\mathcal{T} = \{P^{N_1}, P^{N_2}, \ldots, P^{N_T}\}$ with N_T being the number of timestamped points in $\mathcal{T}$. Here, the N_t-th timestamped point P^{N_t} is denoted as $P^{N_t} = (x^{N_t}, y^{N_t}, t)$ at the time t.

Let $\mathcal{C}_\mathcal{T}$ denote the historical vessel trajectory set, i.e., $\mathcal{C}_\mathcal{T} = \{\mathcal{T}_1, \mathcal{T}_2, \ldots, \mathcal{T}_N\}$ with N being the number of collected trajectories from raw AIS data. In general, the prediction of vessel trajectory can be regarded as learning the projection function $\mathcal{F}$ from large-scale historical vessel trajectories. Then, we can predict the coordinates $(x_n^{N_{\bar{t}}}, y_n^{N_{\bar{t}}})$ of the $N_{\bar{t}}$-th timestamped point $P_n^{\bar{t}}$ in the n-th vessel trajectory at the time $\bar{t}$, which is defined as follows

参考文献：

[54] P. Zhang, J. Xue, P. Zhang, N. Zheng, and W. Ouyang, "Social-aware pedestrian trajectory prediction via states refinement LSTM," *IEEE Trans. Pattern Anal. Mach. Intell.*, to be published, doi: 10.1109/TPAMI.2020.3038217.

[55] L. Fang, Q. Jiang, J. Shi, and B. Zhou, "TPNET: Trajectory proposal network for motion prediction," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2020, pp. 6797–6806.

[56] L. Zhao, Y. Liu, A. Y. Al-Dubai, A. Y. Zomaya, G. Min, and A. Hawbani, "A novel generation-adversarial-network-based vehicle trajectory prediction method for intelligent vehicular networks," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 2066–2077, Feb. 2021.

[57] L. Rossi, M. Paolanti, R. Pierdicca, and E. Frontoni, "Human trajectory prediction and generation using LSTM models and GANS," *Pattern Recognit.*, vol. 120, Dec. 2021, Art. no. 108136.

[58] B. Murray and L. P. Perera, "A dual linear autoencoder approach for vessel trajectory prediction using historical AIS data," *Ocean Eng.*, vol. 209, Aug. 2020, Art. no. 107478.

[59] P. Han, W. Wang, Q. Shi, and J. Yue, "A combined online-learning model with k-means clustering and GRU neural networks for trajectory prediction," *Ad Hoc Netw.*, vol. 117, Jun. 2021, Art. no. 102476.

[60] H. Cheng, F. T. Johora, M. Sester, and J. P. Müller, "Trajectory modelling in shared spaces: Expert-based vs. deep learning approach," in *Proc. Int. Workshop Multi-Agent Syst. Agent-Based Simul.*, 2020, pp. 13–27.

[61] S. Eiffert, K. Li, M. Shan, S. Worrall, S. Sukkarieh, and E. Nebot, "Probabilistic crowd GAN: Multimodal pedestrian trajectory prediction using a graph vehicle-pedestrian attention network," *IEEE Robot. Autom. Lett.*, vol. 5, no. 4, pp. 5026–5033, Oct. 2020.

[62] N. Bisagno, B. Zhang, and N. Conci, "Group LSTM: Group trajectory prediction in crowded scenarios," in *Proc. IEEE Eur. Conf. Comput. Vis.*, 2018, pp. 213–225.

[63] Z. Xiao, L. Zhang, X. Fu, W. Zhang, J. T. Zhou, and R. S. M. Goh, "Concurrent processing cluster design to empower simultaneous prediction for hundreds of vessels' trajectories in near real-time," *IEEE Trans. Syst. Man Cybern.: Syst.*, vol. 51, no. 3, pp. 1830–1843, Mar. 2021.

[64] Y. Hua, Z. Zhao, R. Li, X. Chen, Z. Liu, and H. Zhang, "Deep learning with long short-term memory for time series prediction," *IEEE Commun. Mag.*, vol. 57, no. 6, pp. 114–119, Jun. 2019.

[65] D. Helbing and P. Molnar, "Social force model for pedestrian dynamics," *Phys. Rev. E*, vol. 51, no. 5, pp. 4282–4286, May 1995.

[66] D. P. Kingma and J. Ba, "ADAM: A method for stochastic optimization," in *Proc. Int. Conf. Learn. Representations*, 2015, pp. 1–15.

[67] B. Kim, C. M. Kang, J. Kim, S. H. Lee, C. C. Chung, and J. W. Choi,

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3. 被引论文：A novel prediction-based temporal graph routing algorithm for softwaredefined vehicular networks

引用文献：

[1] Haijun Liao, Zhenyu Zhou, Nian Liu, Yan Zhang, Guangyuan Xu, Zhenti Wang, Shahid Mumtaz, "Cloud-Edge-Device Collaborative Reliable and Communication-Efficient Digital Twin for Low-Carbon Electrical Equipment Management", IEEE Transactions on Industrial Informatics, vol.19, no.2, pp.1715-1724, 2023.

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to improve the reliability and communication efficiency of DT. Compared with the traditional edge-device DT framework and cloud-device DT framework, the cloud-edge-device collaborative DT framework has the advantages of global digitalization and cross-region resource scheduling, DT consistency improvement, and full utilization of cloud-edge-device multidimensional resources.

A two-timescale FL-based model training process is proposed [13]. We consider G epochs, and each epoch consists of T_0 slots. The G epochs contain $T = GT_0$ slots, the set of which is $\mathcal{T} = \{1, \ldots, t, \ldots, T\}$. The edge aggregation-based regional model training is performed in a small timescale, i.e., every slot, while the cloud aggregation-based global model training is performed in a large timescale, i.e., every epoch. The training process has four phases, i.e., model distribution, device-side model training, regional model training, and global model training, which are introduced as follows.

2) Device-Side Model Uploading: There exist N_j orthogonal subchannels, the set of which is denoted as $\mathcal{C}^j = \{c_1^j, \ldots, c_n^j, \ldots, c_{N_j}^j\}$. Denote the channel allocation strategy of s^j as $\boldsymbol{r}^j(t) = \{r_{i,n}^j(t) | \forall u_i^j \forall c_n^j\}$, where $r_{i,n}^j(t) = 1$ represents that s^j allocates c_n^j to u_i^j, and $r_{i,n}^j(t) = 0$, otherwise.

The model uploading delay and energy costs of u_i^j are given by

$$\tau_i^{j,Tx}(t) = \frac{a_i^j(t) S}{\sum_{n=1}^{N} B^U r_{i,n}^j(t) \log_2\left(1 + \frac{P_i^j(t) h_{i,n}^j(t)}{I_i^{j,U}(t) + B^U N_0}\right)},$$

$$E_i^{j,Tx}(t) = \tau_i^{j,Tx}(t) P_i(t), \quad (3)$$

where S is the packet size of the device-side model $\boldsymbol{\omega}_i^j(t)$. B^U is the subchannel bandwidth, $P_i^j(t)$ is the transmission power, and $h_{i,n}^j(t)$ is the uplink channel gain of c_n^j. $I_i^{j,U}(t)$ and N_0 are the EMI power and the noise power spectral density [14].

C. Regional Model Training at Edge Layer

参考文献：

VI. Conclusion

In this article, we addressed the problem of DT unreliability and low communication efficiency for low-carbon electric equipment management. C^3-FLOW was proposed to achieve reliable and communication-efficient DT-assisted cloud-edge-device collaborative resource allocation. Compared with WLFL and DNN-DTFL, C^3-FLOW reduces loss function by 9.78% and 49.28% and reduces communication cost by 14.71% and 8.59%, respectively. Besides, the V2G energy scheduling case verifies that C^3-FLOW can reduce the carbon emission by 36.78% and 64.35% during the peak time, and increase renewable energy absorption by 29.41% and 69.78% during the off-peak time. In future, the heterogeneities of device-side communication and computational resources will be studied to further improve the electrical equipment management performance.

References

[1] J. Pan, R. Jain, S. Paul, T. Vu, A. Saifullah, and M. Sha, "An Internet of Things framework for smart energy in buildings: Designs, prototype, and experiments," *IEEE Internet Things J.*, vol. 2, no. 6, pp. 527–537, Dec. 2015.

[2] J. Qi, L. Liu, Z. Shen, B. Xu, K.-S. Leung, and Y. Sun, "Low-carbon community adaptive energy management optimization toward smart services," *IEEE Trans. Ind. Informat.*, vol. 16, no. 5, pp. 3587–3596, May 2020.

[3] Z. Yang, Y. Fang, G. Han, and K. M. S. Huq, "Spatially coupled protograph LDPC-coded hierarchical modulated BICM-ID systems: A promising transmission technique for 6G-enabled Internet of Things," *IEEE Internet Things J.*, vol. 8, no. 7, pp. 5149–5163, Apr. 2021.

[12] W. Sun, N. Xu, L. Wang, H. Zhang, and Y. Zhang, "Dynamic digital twin and federated learning with incentives for air-ground networks," *IEEE Trans. Netw. Sci. Eng.*, vol. 9, no. 1, pp. 321–333, Jan.–Feb. 2022.

[13] L. Zhao et al., "A novel prediction-based temporal graph routing algorithm for software-defined vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 8, pp. 13275–13290, Aug. 2022.

[14] L. Zhao, T. Zheng, M. Lin, A. Hawbani, J. Shang, and C. Fan, "SPIDER: A social computing inspired predictive routing scheme for softwarized vehicular networks," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 7, pp. 9466–9477, Jul. 2022.

[15] Y. Xi, A. Burr, J. Wei, and D. Grace, "A general upper bound to evaluate packet error rate over quasi-static fading channels," *IEEE Trans. Wireless Commun.*, vol. 10, no. 5, pp. 1373–1377, May 2011.

[16] M. Chen, Z. Yang, W. Saad, C. Yin, H. V. Poor, and S. Cui, "A joint learning and communications framework for federated learning over wireless networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 1, pp. 269–283, Jan. 2021.

[17] G. Cui, Y. Long, L. Xu, and W. Wang, "Joint offloading and resource allocation for satellite assisted vehicle-to-vehicle communication," *IEEE Syst. J.*, vol. 15, no. 3, pp. 3958–3969, Sep. 2021.

[18] L. Zhao, H. Chai, Y. Han, K. Yu, and S. Mumtaz, "A collaborative V2X data correction method for road safety," *IEEE Trans. Rel.*, vol. 71, no. 2, pp. 951–962, Jun. 2022.

[19] V.-D. Nguyen, S. K. Sharma, T. X. Vu, S. Chatzinotas, and B. Ottersten, "Efficient federated learning algorithm for resource allocation in wireless IoT networks," *IEEE Internet Things J.*, vol. 8, no. 5, pp. 3394–3409, Mar. 2021.

[20] Z. Zhou, C. Sun, R. Shi, Z. Chang, S. Zhou, and Y. Li, "Robust energy scheduling in vehicle-to-grid networks," *IEEE Netw.*, vol. 31, no. 2, pp. 30–37, Mar./Apr. 2017.

[21] W. Xia, T. Q. S. Quek, K. Guo, W. Wen, H. H. Yang, and H. Zhu, "Multi-armed bandit-based client scheduling for federated learning," *IEEE Trans. Wireless Commun.*, vol. 19, no. 11, pp. 7108–7123, Nov. 2020.

[22] Y. Lu, X. Huang, K. Zhang, S. Maharjan, and Y. Zhang, "Communication-efficient federated learning and permissioned blockchain for digital twin edge networks," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2276–2288, Feb. 2021.

4.被引论文：Green internet of things using UAVs in B5G networks: A review of applications and strategies

引用文献：

[1] Liudong Xing and Barry W. Johnson, "Reliability Theory and Practice for Unmanned Aerial Vehicles," in IEEE Internet of Things Journal, vol. 10, no. 4, pp. 3548-3566, 15 Feb.15, 2023, doi: 10.1109/JIOT.2022.3218491.

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引用部分：

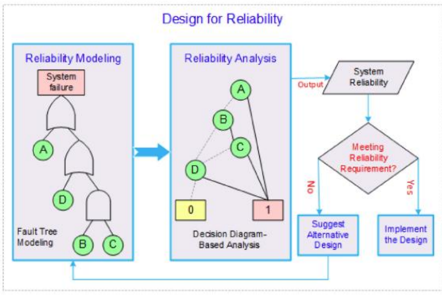

Fig. 1. Illustration of reliability modeling, analysis, and design.

greatly reducing the risk and ensuring the safety of the human workforce [3], [4]. UAVs are also vital for implementing green IoT systems since they can fly close to IoT to significantly reduce energy consumption for transmitting data collected from surroundings [5].

UAVs were originally applied to military use cases, such as reconnaissance and target practice. Due to the technology advancements and cost reduction of wireless communications and smart sensors, UAVs are now being widely deployed in various civil application areas, spanning from film making to scientific research, disaster management to environmental monitoring, agriculture to transportation, healthcare to mining, surveillance to recreation, packet delivery to the construction industry, etc. [5], [6]. According to Insider Intelligence [7], the UAV services market size is expected to reach $63.6 billion by 2025.

The applications of UAVs are typically mission critical,

approaches include for example, simulations [15], [16], and analytical modeling approaches, which further encompass combinatorial approaches (e.g., decision diagrams illustrated in Fig. 1 [17], [18], universal generation functions [19]), state space-oriented approaches (e.g., Markov [20] and semi-Markov [21] processes, petri nets [22]), and event transition-based approaches [14].

Reliability design is a process of selecting appropriate components, redundancy levels, and schemes, as well as robust system configurations to ensure that the reliability requirement can be satisfied during the intended mission time under certain operating environments. Redundancies (in the form of hardware, software, information, and time redundancies [23]) enable a system to tolerate various faults caused by incorrect algorithms, component defects or wear out, external disturbances, etc. However, using redundancies does not guarantee a system design with a high level of reliability. Likewise, a system with high reliability is not necessarily fault tolerant or resilient [2], [24]. Therefore, it is indispensable to conduct reliability modeling and analysis to ensure that the system design developed satisfies the reliability requirement. As demonstrated in Fig. 1, if the design meets the reliability requirement, the design will be implemented; otherwise, alternative designs should be suggested for reliability modeling and analysis.

A rich body of literature exists, covering different aspects of reliability-related research on UAVs. There are also many review articles published on UAVs. For example, in [5], a review of techniques based on the infrastructure of UAVs for achieving green and sustainable industry IoT systems was given. In [6], a review of UAV-assisted services in the IoT environment was given, where four classes of services are differentiated, including UAV-assisted communications, battery charges, data-related services, and mobile edge com-

参考文献：

post-hazard phases (motivated by the three phases for power systems [258]).

As demonstrated in Fig. 9, during the prehazard phase, proactive or PM strategies may be implemented to improve the UAV system's resilience against some predicted shocks or hazards. Examples of such strategies include using materials that can strengthen the system structure and developing encryption-based secure communication protocols against cyberattacks. During the occurrence of a hazard event, the UAV system or network often deteriorates and the performance degradation may be softened via hazard-tolerant maintenance strategies, like redundancies. During the post-hazard phase, restorative or CM strategies (like repairs) may be conducted to bring the failed UAV back to the functioning state if the UAV is not destroyed.

D. Joint-Optimization of Multiple Design Parameters

While reliability is a critical parameter considered for the design and operation of UAVs, other design parameters, such as security, cost, and performance in terms of response time and productivity should also be taken into account. Different design requirements are often conflicting. For example, in the UAV-assisted data communication network, data replica-

REFERENCES

[1] J. A. Stankovic, "Research directions for the Internet of Things," *IEEE Internet Things J.*, vol. 1, no. 1, pp. 3–9, Feb. 2014, doi: 10.1109/JIOT.2014.2312291.

[2] L. Xing, "Reliability in Internet of Things: Current status and future perspectives," *IEEE Internet Things J.*, vol. 7, no. 8, pp. 6704–6721, Aug. 2020, doi: 10.1109/JIOT.2020.299321.

[3] B. Li, Z. Fei, and Y. Zhang, "UAV communications for 5G and beyond: Recent advances and future trends," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019, doi: 10.1109/JIOT.2018.2887086.

[4] D. C. Nguyen et al., "6G Internet of Things: A comprehensive survey," *IEEE Internet Things J.*, vol. 9, no. 1, pp. 359–383, Jan. 2022, doi: 10.1109/JIOT.2021.3103320.

[5] S. H. Alsamhi et al., "Green Internet of Things using UAVs in B5G networks: A review of applications and strategies," *Ad Hoc Netw.*, vol. 117, Jun. 2021, Art. no. 102505. [Online]. Available: https://doi.org/10.1016/j.adhoc.2021.102505

[6] R. Pakrooh and A. Bohlooli, "A survey on unmanned aerial vehicles-assisted Internet of Things: A service-oriented classification," *Wireless Pers. Commun.*, vol. 119, no. 2, pp. 1541–1575, 2021. [Online]. Available: https://doi.org/10.1007/s11277-021-08294-6

[7] Insider Intelligence. "Drone Market Outlook in 2022: Industry Growth Trends, Market Stats and Forecast." Feb. 2, 2022. Accessed: Mar. 2022. [Online]. Available: https://www.businessinsider.com/drone-industry-analysis-market-trends-growth-forecasts

[8] B. Lutkevich and A. R. Earls. "Drone (UAV)." Accessed: Mar. 2022. [Online]. Available: https://internetofthingsagenda.techtarget.com/definition/drone

[2] Shumaila Javaid, Nasir Saeed, Zakria Qadir, Hamza Fahim, Bin He, Houbing Song, Muhammad Bilal, "Communication and Control in Collaborative UAVs: Recent Advances and Future Trends," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 6, pp. 5719-5739, June 2023, doi: 10.1109/TITS.2023.3248841.

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引用部分：

product delivery and disaster relief applications [18], [19]. However, a few primary constraints include lack of physical infrastructure, high mobility, channel characterization, intermittent connectivity, bounded transmission range, and limited resources [10], [20] are hindering the development of collaborative UAV swarm architecture.

Accordingly, existing studies address the aforementioned issues by focusing on different solutions, including channel characterization, resource management, data communication, and emerging technologies integration (such as 5G and 6G) to enable fast and reliable collaborative UAV communications. For example, in [21], Li et al. highlighted the advancement of 5G-assisted UAV communication for achieving high reliability, fast speed, rapid recovery, flexibility, and cost-effective traffic offloading in highly crowded areas. In another work [22], authors identified the limitations of UAV communication (such as Line of Sight (LoS) dominant UAV-ground channel, high Quality of Service (QoS) requirements, and inadequate power, size and weight constraints) that can be addressed using 5G and beyond 5G technology. A few recent studies [1], [2], [23], [24], [25], investigated the 5G millimeter-wave communication and the scope of 5G aided UAV communication for channel characterization, standardization, collision avoidance, energy efficiency, and optimal trajectory design.

A. Related Surveys

Due to emerging applications of UAVs, various surveys in the literature cover different aspects of UAVs. For instance, In [25], a detailed review of communication networks and routing protocols are presented that highlight their contribution to improve the reliability, data delivery, and resource optimization of UAV networks. Authors in [24] investigated the potential of UAVs for enhancing the performance of wireless networks in terms of coverage, energy efficiency, capacity, and reliability. In another survey [26], Khuwaja et al. reviewed

object tracking, path planning, navigation, monitoring and data manipulation that a swarm of UAVs can perform. However, the authors did not include a comprehensive discussion on collaborative communication architecture and mechanisms for performing distributed operations. Nawaz et al. in [31] discussed the characteristics of a UAV network compared to WSN and mobile ad-hoc networks and summarized the network issues (such as routing, power and quality of service) that need to be addressed for collaborative UAV networks. However, the presented review did not discuss the UAV's collaborative tasks in detail. In another work [20], authors comprehensively studied the UAV communication links (such as UAV-to-UAV and UAV-to-infrastructure) to identify the requirements of UAV-based communication systems. However, the detailed review of the networking architectures and communication framework did not include the UAV collaboration for joint control and task completion. In [32], authors studied the UAV's role in achieving green Internet of Things (IoT) to realize a sustainable smart world. The survey summarizes strategies to integrate UAVs with IoT as edge intelligence devices to collect and process data obtained from IoT devices. The review also explores the opportunities for connectivity and communication beyond 5G. However, it did not include UAV-to-UAV communication for collaborative control and task performance. In another work [33], Shi et al. in reviewed the existing UAV communication protocols for power line inspection industry and classified the UAV communication link type and summarized the wireless mesh networking protocols; however, it lacks focus on the existing schemes related to collaborative UAV communication.

In [34], the authors reviewed machine learning techniques for UAV communication and provided an overview for integrating machine learning techniques that can optimize the physical layer and improve resource and network management. Furthermore, Hayat et al. in [35] studied the civil applications of UAVs and discussed QoS and data communication require-

参考文献：

[31] H. Nawaz, H. M. Ali, and A. A. Laghari, "UAV communication networks issues: A review," *Arch. Comput. Methods Eng.*, vol. 28, no. 3, pp. 1349–1369, May 2021.

[32] S. H. Alsamhi et al., "Green Internet of Things using UAVs in B5G networks: A review of applications and strategies," *Ad Hoc Netw.*, vol. 117, Jun. 2021, Art. no. 102505.

[33] L. Shi, N. J. H. Marcano, and R. H. Jacobsen, "A review on communication protocols for autonomous unmanned aerial vehicles for inspection application," *Microprocessors Microsyst.*, vol. 86, Oct. 2021, Art. no. 104340.

[34] P. S. Bithas, E. T. Michailidis, N. Nomikos, D. Vouyioukas, and A. G. Kanatas, "A survey on machine-learning techniques for UAV-based communications," *Sensors*, vol. 19, no. 23, p. 5170, 2019.

[35] S. Hayat, E. Yanmaz, and R. Muzaffar, "Survey on unmanned aerial vehicle networks for civil applications: A communications viewpoint," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 4, pp. 2624–2661, 4th Quart., 2016.

[36] T. Adão et al., "Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry," *Remote Sens.*, vol. 9, no. 11, p. 1110, 2017.

[52] F. A. D'Oliveira, F. C. L. D. Melo, and T. C. Devezas, "High-altitude platforms–present situation and technology trends," *J. Aerosp. Technol. Manage.*, vol. 8, no. 3, pp. 249–262, Aug. 2016.

[53] S. Morosi, S. Jayousi, E. Falletti, and G. Araniti, "Cooperative strategies in satellite assisted emergency services," *Int. J. Satell. Commun. Netw.*, vol. 31, no. 3, pp. 141–156, May 2013.

[54] F. Dong, H. Li, X. Gong, Q. Liu, and J. Wang, "Energy-efficient transmissions for remote wireless sensor networks: An integrated HAP/satellite architecture for emergency scenarios," *Sensors*, vol. 15, no. 9, pp. 22266–22290, Sep. 2015.

[55] D. Yuniarti, "Regulatory challenges of broadband communication services from high altitude platforms (HAPs)," in *Proc. Int. Conf. Inf. Commun. Technol. (ICOIACT)*, Mar. 2018, pp. 919–922.

[56] D. He, S. Chan, and M. Guizani, "Communication security of unmanned aerial vehicles," *IEEE Wireless Commun.*, vol. 24, no. 4, pp. 134–139, Aug. 2017.

[57] Z. Becvar, M. Vondra, P. Mach, J. Plachy, and D. Gesbert, "Performance of mobile networks with UAVs: Can flying base stations substitute ultra-dense small cells?" in *Proc. Eur. Wireless, 23th Eur. Wireless Conf.* Dresden, Germany: VDE, 2017, pp. 1–7.

[3] Abegaz Mohammed Seid, Hayla Nahom Abishu, Yasin Habtamu Yacob, Tewodros Alemu Ayall, Aiman Erbad, Mohsen Guizani, "Blockchain-Based Resource Trading in Multi-UAV-Assisted Industrial IoT Networks: A Multi-Agent DRL Approach," in IEEE Transactions on Network and Service Management, vol. 20, no. 1, pp. 166-181, March 2023, doi: 10.1109/TNSM.2022.3197309.

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引用部分：

no physical infrastructure coverage [20], [21], [22], [23], [24]. Besides, UAVs are actively used in mission-critical services such as military, emergency communication, and health care due to their low implementation cost, short-range line-of-sight connection, and capacity to execute jobs like delivery services, disaster relief, and agriculture applications that humans cannot easily perform [25], [26], [27]. These UAVs provide flexible short-distance wireless communication, allowing the collection and dissemination of information at a minimal cost. Moreover, the rapid deployment and relocating capabilities of UAVs also enable them to automatically adapt to dynamic and emerging communication requirements, improving fault tolerance and resilience in IIoT systems.

Furthermore, several studies have proposed solutions for resource trading in IIoT networks to address the resource limitations of MDs. Traditional resource-sharing approaches cannot achieve the desired performance due to the dynamic nature of the IIoT environment and the resource limitations of MDs. Moreover, the IIoT mandates that resource sharing policies be intelligent enough to make intelligent resource access decisions [28], [29]. In this regard, machine learning (ML) is one of the most powerful data-driven approaches for enabling intelligent decision-making by using a massive amount of data from multiple heterogeneous IIoT devices [30]. In recent years, researchers have applied ML approaches to the problem of dynamic resource allocation and sharing, such as single-agent reinforcement learning (RL) and deep reinforcement learning (DRL) [31], [32], [33], [34]. However, in a complex and multi-agent system, a single agent RL/DRL approach does not achieve various optimization problems [35]. Thus, multi-agent reinforcement learning algorithms (MARL) have

is used for intelligent decision-making policy to maximize the benefits for both MDs and UAVs. The UAVs affordably lease spectrum and energy resources to the MDs via wireless communication systems, and the MDs can then efficiently interact in the network to improve the performance of the industrial system. It can significantly improve the performance of the IIoT communication system. The main contributions of this paper are as follows:

- We propose a novel resource trading framework that integrates multi-agent DRL (MADRL) with consortium blockchain and the Stackelberg game. In this framework, UAVs act as ABS to lease resources such as spectrum and energy to the MDs deployed in the IIoT ecosystem. We formulate utility maximization problem as a two stage multi-leader-multi-followers (MLMF) Stackelberg game to allow resource sellers/UAVs and resource buyers/MDs to maximize the aggregate reward and improve resource trading efficiency.
- We model the optimization problem as an extended Markov decision process (MDP)/stochastic game to handle the dynamic resource trading problems of multi-UAV-assisted IIoT networks, in which each UAV and MD acts as a learning agent and each resource trading solution corresponds to a UAV and MD action.
- We adopt a dynamic pricing algorithm that combines the Stackelberg game with MADDPG algorithm, namely, Stackelberg MADDPG (SMADDPG) to solve the formulated stochastic game of multi-UAV-assisted IIoT networks. It allows UAVs to integrate spectrum and energy strategic planning to increase their utilities while meeting the QoS requirements of various MDs.

参考文献：

[22] H. Ke, H. Wang, W. Sun, and H. Sun, "Adaptive computation offloading policy for multi-access edge computing in heterogeneous wireless networks," *IEEE Trans. Netw. Service Manag.*, vol. 19, no. 1, pp. 289–305, Mar. 2022.
[23] N. H. Motlagh, T. Taleb, and O. Arouk, "Low-altitude unmanned aerial vehicles-based Internet of Things services: Comprehensive survey and future perspectives," *IEEE Internet Things J.*, vol. 3, no. 6, pp. 899–922, Dec. 2016.
[24] Z. Zhao *et al.*, "Predictive UAV base station deployment and service offloading with distributed edge learning," *IEEE Trans. Netw. Service Manag.*, vol. 18, no. 4, pp. 3955–3972, Dec. 2021.
[25] M. Mozaffari, W. Saad, M. Bennis, Y.-H. Nam, and M. Debbah, "A tutorial on UAVs for wireless networks: Applications, challenges, and open problems," *IEEE Commun. Surveys Tuts.*, vol. 21, no. 3, pp. 2334–2360, 3rd Quart., 2019.
[26] T. Yuan, C. E. Rothenberg, K. Obraczka, C. Barakat, and T. Turletti, "Harnessing UAVs for fair 5G bandwidth allocation in vehicular communication via deep reinforcement learning," *IEEE Trans. Netw. Service Manag.*, vol. 18, no. 4, pp. 4063–4074, Dec. 2021.
[27] S. H. Alsamhi *et al.*, "Green Internet of Things using UAVs in B5G networks: A review of applications and strategies," *Ad Hoc Netw.*, vol. 117, Jun. 2021, Art. no. 102505.
[28] W. Zhang *et al.*, "Deep reinforcement learning based resource management for DNN inference in IIoT," in *Proc. IEEE Global Commun. Conf.*, 2020, pp. 1–6.
[43] C. Ma *et al.*, "Cooperative spectrum sharing in D2D-enabled cellular networks," *IEEE Trans. Commun.*, vol. 64, no. 10, pp. 4394–4408, Oct. 2016.
[44] M. K. Farshbafan, M. H. Bahonar, and F. Khaiehraveni, "Spectrum trading for device-to-device communication in cellular networks using incomplete information bandwidth-auction game," in *Proc. 27th Iran. Conf. Elect. Eng. (ICEE)*, 2019, pp. 1441–1447.
[45] J. Qiu, D. Grace, G. Ding, J. Yao, and Q. Wu, "Blockchain-based secure spectrum trading for unmanned-aerial-vehicle-assisted cellular networks: An operator's perspective," *IEEE Internet Things J.*, vol. 7, no. 1, pp. 451–466, Jan. 2020.
[46] L. Xue, W. Yang, W. Chen, and L. Huang, "STBC: A novel blockchain-based spectrum trading solution," *IEEE Trans. Cogn. Commun. Netw.*, vol. 8, no. 1, pp. 13–30, Mar. 2022.
[47] Z. Liu, D. Wang, J. Wang, X. Wang, and H. Li, "A blockchain-enabled secure power trading mechanism for smart grid employing wireless networks," *IEEE Access*, vol. 8, pp. 177745–177756, 2020.
[48] X. Lin, J. Wu, A. K. Bashir, J. Li, W. Yang, and J. Piran, "Blockchain-based incentive energy-knowledge trading in IoT: Joint power transfer and AI design," *IEEE Internet Things J.*, early access, Sep. 15, 2020, doi: 10.1109/JIOT.2020.3024246.
[49] M. J. A. Baig, M. T. Iqbal, M. Jamil, and J. Khan, "IoT and blockchain based peer to peer energy trading pilot platform," in *Proc. 11th IEEE Annu. Inf. Technol. Electron. Mobile Commun. Conf. (IEMCON)*, 2020, pp. 402–406.

5.被引论文：Novel online sequential learning-based adaptive routing for edge softwaredefined vehicular networks

引用文献：

[1] Bin Li, Yufeng Liu, Ling Tan, Heng Pan, Yan Zhang, "Digital Twin Assisted Task Offloading for Aerial Edge Computing and Networks," in IEEE Transactions on Vehicular Technology, vol. 71, no. 10, pp. 10863-10877, Oct. 2022, doi: 10.1109/TVT.2022.3182647.

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引用部分：

Digital Twin Assisted Task Offloading for Aerial Edge Computing and Networks

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***Abstract*—Considering the user mobility and unpredictable mobile edge computing (MEC) environments, this paper studies the intelligent task offloading problem in unmanned aerial vehicle (UAV)-enabled MEC with the assistance of digital twin (DT). We aim at minimizing the energy consumption of the entire MEC system by jointly optimizing mobile terminal users (MTUs) association, UAV trajectory, transmission power distribution and computation capacity allocation while respecting the constraints of mission maximum processing delays. Specifically, double deep Q-network (DDQN) algorithm stemming from deep reinforcement learning is first proposed to effectively solve the problem of MTUs association and UAV trajectory. Then, the closed-form expression is employed to handle the problem of transmission power distribution and the computation capacity allocation problem is further addressed via an iterative algorithm. Numerical results show that our proposed scheme is able to converge and significantly reduce the total energy consumption of the MEC system compared to the benchmark schemes.**

***Index Terms*—Digital twin, unmanned aerial vehicle, mobile edge computing, user mobility, deep reinforcement learning.**

I. Introduction

The proliferation of a variety of mobile services with rich experiences may bring unprecedented challenges to the computational performance of mobile devices due to their restricted calculation ability [1]–[3]. Although mobile edge computing (MEC) technology has been envisioned as a revolutionary solution to realize the ability of cloud computing at the edge of the networks [4]–[6], there are still some deficiencies to be tackled, i.e., the location limitations of static ground base station (BS) and high deployment cost. Owing to the flexible deployment and low price of unmanned aerial vehicles (UAVs) [7], [8], UAVs as MEC nodes have emerged as a key advocate for providing mobile-edge services in 5G emergency communications.

A number of research efforts have been dedicated to the UAV-enabled MEC for task offloading. For instance, in [9], given the size of the calculation tasks and the deadline for completion, the authors considered the computation resources and UAV trajectory to minimize the weighted system energy consumption. In [10], constrained by UAV's limited energy, the authors focused on applying UAV as an aerial BS to provide computational task offloading services to the ground users for maximizing migration throughput of user tasks. The authors in [11] investigated the total energy consumption of user equipments by jointly optimizing users' association, uplink power control, and UAV 3-D placement, etc. Nevertheless, the UAV-assisted MEC network also faces new challenges, i.e., the long line-of-sight (LoS) link [12] between user and UAV will cause long transmission time and the computing resource at UAV is not always adequate, which are not friendly to the delay-sensitive tasks.

Benefiting from the proximity gain, device-to-device (D2D) communications have brought much attention in wireless research community. Recently, there has been growing interest

参考文献：

To handle the design optimization problem, the DDQN algorithm was successfully applied to realize intelligent offloading of MTUs tasks and UAV deployment. Furthermore, the closed-form expression was derived to quickly get the optimal transmission power distribution and an efficient iterative algorithm was used to achieve the computation capacity allocation of multiple MTUs, resource devices and UAV. Finally, numerical results were conducted to show that our proposed design can reduce the whole MEC system energy consumption by 7%, 11% and 59% compared with the DQN design, Without optimize F design and Greedy design, respectively. In future work, we will take into account the multi-device wireless interference model for a large number of devices.

Appendix A

The energy consumption of MTU m associated with UAV j is given by

$$E^{\mathrm{UAV}}_m[n] = p^{\mathrm{UAV}}_m[n] T^{\mathrm{UAV}}_m[n] = p^{\mathrm{UAV}}_m[n] \frac{D_m[n]}{\cdots}$$

References

[1] K. Guo, R. Gao, W. Xia, and T. Q. S. Quek, "Online learning based computation offloading in MEC systems with communication and computation dynamics," *IEEE Trans. Commun.*, vol. 69, no. 2, pp. 1147–1162, Feb. 2021.

[2] T. D. T. Nguyen, V. Nguyen, V.-N. Pham, L. N. T. Huynh, M. D. Hossain, and E.-N. Huh, "Modeling data redundancy and cost-aware task allocation in MEC-enabled internet-of-vehicles applications," *IEEE Internet Things J.*, vol. 8, no. 3, pp. 1687–1701, Feb. 2021.

[3] L. Zhao, W. Zhao, A. Hawbani, A. Y. Al-Dubai, and C. Gong, "Novel online sequential learning-based adaptive routing for edge software-defined vehicular networks," *IEEE Trans. Wireless Commun.*, vol. 20, no. 5, pp. 2991–3004, May 2021.

[4] Z. Song, Y. Liu, and X. Sun, "Joint task offloading and resource allocation for NOMA-enabled multi-access mobile edge computing," *IEEE Trans. Commun.*, vol. 69, no. 3, pp. 1548–1564, Mar. 2021.

[5] P. A. Apostolopoulos, G. Fragkos, E. E. Tsiropoulou, and S. Papavassiliou, "Data offloading in UAV-assisted multi-access edge computing systems under resource uncertainty," *IEEE Trans. Mobile Comput.*, to be published, doi: 10.1109/TMC.2021.3069911.

[6] X. Huang, S. Leng, S. Maharjan, and Y. Zhang, "Multi-agent deep reinforcement learning for computation offloading and interference coordination in small cell networks," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9282–9293, Sep. 2021.

6. 被 引 论 文 ： Drones’ edge intelligence over smart environments in B5G: Blockchain and federated learning synergy

引用文献：

[1] Bomin Mao, Jiajia Liu, Yingying Wu, Nei Kato, "Security and Privacy on 6G Network Edge: A Survey," in IEEE Communications Surveys & Tutorials, vol. 25, no. 2, pp. 1095-1127, Secondquarter 2023, doi: 10.1109/COMST.2023.3244674.

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引用部分：

driving field, blockchain has been considered to guarantee the secure billing data transmissions between electric vehicles and grid [126], [127]. Combined with edge intelligence, blockchain can be used to protect the traffic light control system against the malicious attacks [128]. In the information-centric networks, blockchain can not only improve the reliability of edge caching resource [81], but also guarantee the secure content delivery against malevolent tampering [129].

Blockchain-secured federated learning: As we introduced above, the global model in FL can be poisoned by unreliable local participants since they can falsify the data or submit the incorrect model, which is termed Byzantine attacks [66]. FL can be combined with blockchain to enhance the data security on the network edge as blockchain can provide the blocks to store the data for tracing in a decentralized manner [64], [67], [130]. The survey paper [50] introduces the research on blockchain-secured FL. And it can be found that the techniques including edge computing, edge caching, and edge intelligence are popular application scenarios of blockchain-secured FL. In the edge computing field, blockchain has been utilized to select the computing nodes as FL participants [131], prevent edge computing nodes from malfunctioning [64], and optimize the FL-based task offloading [132]. Moreover, the blockchain-secured FL has been illustrated efficient to guarantee the accuracy of local model to realize edge intelligence [133], [134] as shown in Fig. 3. Even though blockchain is mainly used to enhance the security protection, the privacy concern can be still alleviated by this technique when using in the edge caching systems [135].

2) Limitations and Countermeasures: Blockchain has been illustrated to enhance the security of FL. On the other hand,

C. Open-Radio Access Network

As we mentioned in the introduction, the service provision should be transferred from the cloud servers to the network edge to meet the stringent requirements in 6G, for which the interfaces and resources of access network architecture should be available for the service providers. However, as the infrastructure of existing RAN provided by only several vendors are monolithic, network operators treat them as black-box in daily government and application. This causes significant difficulties in meeting diversified requirements, let alone the provision of new business. To address these issues, the O-RAN Alliance was initiated in 2018 by several operators and vendors aiming at standardizing a new access network architecture [139] where the techniques of SDN and NFV are utilized to isolate the network software from the hardware to improve the flexibility. Another motivation behind O-RAN is the emerging need to adopt AI to realize automatic network configurations on the network edge.

The logical architecture of O-RAN is mainly composed of three parts: Service Management and Orchestration (SMO) framework, O-RAN Network Functions, and the O-Cloud platforms [140]. The O-RAN Network Functions is the core of RAN and is extended from 5G RAN. The O-Cloud platform is to run the O-RAN based on the infrastructure including proprietary and general software and hardware, cloud components, and related management/orchestration functions. Since the O-RAN infrastructure can be produced by various vendors, the SMO framework consists of different Operation Administration and Maintenance (OAM) functions from multiple manufacturers, which is much more complex

参考文献：

ized data," in Proc. 20th Int. Conf. Artif. Intell. Stat., vol. 54, Apr. 2017, pp. 1273–1282.

[106] P. Yu, L. Wynter, and S. H. Lim, "FED+: A family of fusion algorithms for federated learning," 2020, *arxiv.abs/2009.06303*.

[107] V. Mothukuri, P. Khare, R. M. Parizi, S. Pouriyeh, A. Dehghantanha, and G. Srivastava, "Federated learning-based anomaly detection for IoT security attacks," *IEEE Internet Things J.*, vol. 9, no. 4, pp. 2545–2554, Feb. 2022, doi: 10.1109/JIOT.2021.3077803.

[108] T. G. Dietterichl, *Ensemble Learning*. Cambridge, MA, USA: MIT Press, 2002.

[109] T. G. Nguyen, T. V. Phan, D. T. Hoang, T. N. Nguyen, and C. So-In, "Federated deep reinforcement learning for traffic monitoring in SDN-based IoT networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 7, no. 4, pp. 1048–1065, Dec. 2021.

[110] J. Han et al., "Deep learning for mobile mental health: Challenges and recent advances," *IEEE Signal Process. Mag.*, vol. 38, no. 6, pp. 96–105, Nov. 2021.

[111] T. A. Khoa, D.-V. Nguyen, M.-S. Dao, and K. Zettsu, "Fed xData: A federated learning framework for enabling contextual health monitoring in a cloud-edge network," in *Proc. IEEE Int. Conf. Big Data (Big Data)*, Orlando, FL, USA, Dec. 2021, pp. 4979–4988.

[112] Q. Wu, K. He, and X. Chen, "Personalized federated learning for intelligent IoT applications: A cloud-edge based framework," *IEEE Open J. Comput. Soc.*, vol. 1, pp. 35–44, 2020.

[113] Y. Gao, L. Liu, X. Zheng, C. Zhang, and H. Ma, "Federated sensing: Edge-cloud elastic collaborative learning for intelligent sensing," *IEEE Internet Things J.*, vol. 8, no. 14, pp. 11100–11111, Jul. 2021.

[114] X. Huang, P. Li, R. Yu, Y. Wu, K. Xie, and S. Xie, "FedParking: A federated learning based parking space estimation with parked vehicle assisted edge computing," *IEEE Trans. Veh. Technol.*, vol. 70, no. 9, pp. 9355–9368, Sep. 2021.

[115] Z. Yu, J. Hu, G. Min, Z. Wang, W. Miao, and S. Li, "Privacy-preserving federated deep learning for cooperative hierarchical caching in fog computing," *IEEE Internet Things J.*, vol. 9, no. 22, pp. 22246–22255, Nov. 2022.

[116] Z. Yu, J. Hu, G. Min, Z. Zhao, W. Miao, and M. S. Hossain

[128] P. Zeng, X. Wang, H. Li, F. Jiang, and R. Doss, "A scheme of intelligent traffic light system based on distributed security architecture of blockchain technology," *IEEE Access*, vol. 8, pp. 33644–33657, 2020.

[129] G. Li, M. Dong, L. T. Yang, K. Ota, J. Wu, and J. Li, "Preserving edge knowledge sharing among IoT services: A blockchain-based approach," *IEEE Trans. Emerg. Topics Comput. Intell.*, vol. 4, no. 5, pp. 653–665, Oct. 2020.

[130] J. Kang et al., "Communication-efficient and cross-chain empowered federated learning for artificial intelligence of things," *IEEE Trans. Netw. Sci. Eng.*, vol. 9, no. 5, pp. 2966–2977, Sep./Oct. 2022.

[131] M. Shen et al., "Exploiting unintended property leakage in blockchain-assisted federated learning for intelligent edge computing," *IEEE Internet Things J.*, vol. 8, no. 4, pp. 2265–2275, Feb. 2021.

[132] G. Qu, N. Cui, H. Wu, R. Li, and Y. Ding, "ChainFL: A simulation platform for joint federated learning and blockchain in edge/cloud computing environments," *IEEE Trans. Ind. Informat.*, vol. 18, no. 5, pp. 3572–3581, May 2022.

[133] S. H. Alsamhi et al., "Drones' edge intelligence over smart environments in B5G: Blockchain and federated learning synergy," *IEEE Trans. Green Commun. Netw.*, vol. 6, no. 1, pp. 295–312, Mar. 2022, doi: 10.1109/TGCN.2021.3132561.

[134] B. Ghimire and D. B. Rawat, "Secure, privacy preserving and verifiable federating learning using blockchain for Internet of Vehicles," *IEEE Consum. Electron. Mag.*, vol. 11, no. 6, pp. 67–74, Nov. 2022, doi: 10.1109/MCE.2021.3097705.

[135] L. Cui et al., "CREAT: Blockchain-assisted compression algorithm of federated learning for content caching in edge computing," *IEEE Internet Things J.*, vol. 19, no. 16, pp. 14151–14161, Aug. 2022, doi: 10.1109/JIOT.2020.3014370.

[136] Y. Xiao, N. Zhang, W. Lou, and Y. T. Hou, "A survey of distributed consensus protocols for blockchain networks," *IEEE Commun. Surveys Tuts.*, vol. 22, no. 2, pp. 1432–1465, 2nd Quart., 2020.

[137] "Bitcoin Network Power Demand." Accessed: Oct. 2021. [Online]. Available: https://ccaf.io/cbeci/index

7.被引论文：Computing in the sky: A survey on intelligent ubiquitous computing for uavassisted 6g networks and industry 4.0/5.0

引用文献：

[1] Yixin He, Fanghui Huang, Dawei Wang, Ruonan Zhang , Xin Gu, Jianping Pan , "NOMA- and MRC-Enabled Framework in Drone-Relayed Vehicular Networks: Height/Trajectory Optimization and Performance Analysis," in IEEE Internet of Things Journal, vol. 10, no. 24, pp. 22305-22319, 15 Dec.15, 2023, doi: 10.1109/JIOT.2023.3303413.

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based on which an NOMA- and MRC-enabled framework is proposed. Next, to fully exploit the advantages of the proposed framework, we separately formulate the total achievable data rate maximization and energy consumption minimization problems by jointly considering the height and 2-D trajectory optimization of relaying drone. The formulated energy consumption minimization problem is transformed into a trajectory optimization problem with obstacle avoidance constraints. Then, for the total achievable data rate maximization problem, we utilize the golden section method to design a height optimization scheme with polynomial complexity. Afterward, we improve the particle swarm optimization (PSO) algorithm, and present an effective 2-D optimization scheme. In addition, the performance superiority of the proposed NOMA- and MRC-enabled framework is analyzed theoretically. Finally, simulation results verify the efficacy of the proposed height and trajectory optimization schemes. For instance, by using the NOMA and MRC techniques, the total achievable data rate can be improved by 24.4%. Moreover, within the same running time, a shorter trajectory can

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I. Introduction

From the first generation (1G) to fifth generation (5G), mobile communication technologies have achieved a global revolution in a short span of time [1]. By using 5G, it is expected to achieve high-speed, high-capacity, low-latency, and massive connectivity [2]. A grand vision is that vehicular networks (VNets), supported by 5G-and-beyond (B5G) networks, will be a key enabler of Intelligent Transportation Systems (ITS) [3]. Although 5G networks are already starting to be used by mobile and smart devices around the world, there are still some technical challenges [4], [5], [6]. For example, in Non-Line-of-Sight (NLoS) scenarios, 5G networks cannot provide good coverage for cell-edge vehicles, especially when trees, buildings, mountains, etc. block the communication links between the remote base station (BS) and cell-edge vehicles. Moreover, how to provide seamless connectivity for rural highways or suburban areas is a key technical difficulty. Due to geographical limitations, widespread deployment of BSs or road side unit (RSU) is not economically viable [7], [8].

Facing these challenges, the communication infrastructure has been elevated from the ground to air, where drones are expected to be significant supplementary components of the ITS-oriented VNets [9]. Specifically, drones can help build high-quality vehicular communication systems and provide a variety of services for smart cities, which have been widely used for data dissemination, data acquisition, traffic detection, etc. [10], [11], [12]. For rural highways, utilizing the drone as a cooperative relay is a promising approach for improving the achievable data rate of cell-edge vehicles and extending the coverage range of cellular networks [13]. By cooperating

参考文献：

VII. Conclusion

In order to improve the achievable data rate of cell-edge vehicles in rural highway scenarios, we in this article proposed a drone-relayed vehicular networking architecture. First, by introducing an NOMA- and MRC-enabled framework, we presented a novel DF relay protocol. Next, we aimed to maximize the total achievable data rate of cell-edge vehicles and meanwhile minimize the energy consumption of relaying drone. More specifically, we formulated a total achievable data rate maximization problem by optimizing the height of relaying drone. In addition, by jointly considering the obstacle avoidance requirements and trajectory optimization, we formulated an energy consumption minimization problem. Then, we used the golden section method and the improved PSO algorithm to solve the formulated problems effectively, based on which the complexity of our designed height and 2-D trajectory optimization schemes was analyzed. Afterward, we

[10] K. Schweiger and L. Preis, "Urban air mobility: Systematic review of scientific publications and regulations for vertiport design and operation," *Drones*, vol. 6, no. 7, p. 179, Jul. 2022.

[11] D. Wang, Y. He, K. Yu, G. Srivastava, L. Nie and R. Zhang, "Delay sensitive secure NOMA transmission for hierarchical HAP-LAP medical-care IoT networks," *IEEE Trans. Ind. Informat.*, vol. 18, no. 8, pp. 5561–5572, Aug. 2022.

[12] S. H. Alsamhi et al., "Computing in the sky: A survey on intelligent ubiquitous computing for UAV-assisted 6G networks and industry 4.0/5.0," *Drones*, vol. 6, no. 7, p. 177, Jul. 2022.

[13] D. Wang, F. Zhou, W. Lin, Z. Ding, and N. Al-Dhahir, "Cooperative hybrid non-orthogonal multiple access based mobile-edge computing in cognitive radio networks," *IEEE Trans. Cogn. Commun. Netw.*, vol. 8, no. 2, pp. 1104–1117, Jun. 2022.

[14] D. Wang, M. Wu, Z. Wei, K. Yu, L. Min, and S. Mumtaz, "Uplink secrecy performance of RIS-based RF/FSO three-dimension heterogeneous networks," *IEEE Trans. Wireless Commun.*, early access, Jul. 12, 2023, doi: 10.1109/TWC.2023.3292073.

[15] J. Zhang et al., "A four-dimensional space-time automatic obstacle avoidance trajectory planning method for multi-UAV cooperative formation flight," *Drones*, vol. 6, no. 8, p. 192, Aug. 2022.

[16] Z. Liu, G. Huang, Q. Zhong, H. Zheng, and S. Zhao, "UAV-aided vehicular communication design with vehicle trajectory's prediction," *IEEE Wireless Commun. Lett.*, vol. 10, no. 6, pp. 1212–1216, Jun. 2021.

[2] Yu Min Park, Sheikh Salman Hassan, Yan Kyaw Tun, Zhu Han, Choong Seon Hong, "Joint Trajectory and Resource Optimization of MEC-Assisted UAVs in Sub-THz Networks: A Resources-Based Multi-Agent Proximal Policy Optimization DRL With Attention Mechanism," in IEEE Transactions on Vehicular Technology, doi: 10.1109/TVT.2023.3311537.

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引用部分：

years, including robots, autonomous cars, gaming, energy management, and others [37]. It has been demonstrated to be a successful solution to resource allocation issues. In real-world situations, agents regularly collaborate to achieve the same goal. Single-agent RL techniques might fail or perform sub-optimally in these environments for various reasons, including partial observability in multi-agent systems, which is exacerbated by increasing the number of agents. MARL claims to tackle these issues with its decentralized execution and centralized training paradigm. In this paradigm, agents make judgments based on local observations, but training entails utilizing all publicly accessible knowledge.

One widely held belief in the MARL literature is that we will only train a limited number of agents, which is incorrect for many real-world MARL applications. Agents in a cooperative video game, for example, may "generate" (i.e., be generated) or "dead" throughout a single episode (i.e., end before the other agents). For example, a group of robots may run out of battery power, forcing one to terminate its journey before the other. In general, an agent can terminate prematurely, implying that it ceases to affect the environment or other agents in the middle of an episode. Furthermore, extra agents can be recruited during an episode.

Existing algorithms often address these scenarios by putting inactive agents in absorbing states. Regardless of action choice, an agent stays absorbing until the entire collection of agents reaches a termination condition. Absorbing states

timizing resources. The locations of MEC-UAV $v \in \mathcal{V}$ and MU u are $l_v^n = [x_v^n, y_v^n, h_0]^T$ and $l_u^n = [x_u^n, y_u^n]^T$ at the time slot n. Furthermore, each MU $u \in \mathcal{U}$ has delay-sensitive computation task at each time slot n as $\Psi_u(n)$, which can be defined as the tuple $\Psi_u(n) = \{D_u^{\text{pre}}(n), C_u^{\text{min}}\}$ $\forall u \in \mathcal{U}$, $\forall n \in \mathcal{N}$, where $D_u^{\text{pre}}(n)$ is the task's input data size and C_u^{min} is the minimum CPU cycles to calculate the task data. It is difficult for MUs to compute their task locally due to the restricted computation capability of each MU and the delay limitation of the tasks. As a result, MU can transfer a portion of their tasks to MEC-UAVs over a THz-band communication link to conduct remote computing. In this work, MEC-UAVs are designed to operate in open environments and are deployed at the same altitude, usually higher than the blockages (buildings, trees, etc.). Therefore, it is reasonable to assume that the LoS communications between MEC-UAVs and UEs will be dominant in the scenario of this paper [40].

B. Local Computation Model

For remote computation, we define a decision variable as a $\alpha_u^v(n)$, which is a proportion of MU u's task data that need to offload to MEC-UAV v at each time slot n. After that the proportion of the task data that computes at MU u at time slot n can be defined as follows:

$$D_u^{\text{in}}(n) = (1 - \alpha_u(n))D_u^{\text{pre}}(n). \qquad (1)$$

After obtaining the proportion of task data $D_u^{\text{in}}(n)$ for local

参考文献：

"Comparing deep reinforcement learning algorithms' ability to safely navigate challenging waters," *Frontiers in Robotics and AI*, vol. 8, Sep. 2021.

[36] W. Mao, L. Yang, K. Zhang, and T. Basar, "On improving model-free algorithms for decentralized multi-agent reinforcement learning," in *International Conference on Machine Learning*, Maryland, USA, Jul. 2022.

[37] Y. Ye, Y. Tang, H. Wang, X.-P. Zhang, and G. Strbac, "A scalable privacy-preserving multi-agent deep reinforcement learning approach for large-scale peer-to-peer transactive energy trading," *IEEE Transactions on Smart Grid*, vol. 12, no. 6, pp. 5185–5200, Aug. 2021.

[38] I.-J. Liu, U. Jain, R. A. Yeh, and A. Schwing, "Cooperative exploration for multi-agent deep reinforcement learning," in *International Conference on Machine Learning*, Online, Jul. 2021.

[39] J. Cui, Y. Liu, and A. Nallanathan, "Multi-agent reinforcement learning-based resource allocation for UAV networks," *IEEE Transactions on Wireless Communications*, vol. 19, no. 2, pp. 729–743, Aug. 2020.

[40] S. H. Alsamhi, A. V. Shvetsov, S. Kumar, J. Hassan, M. A. Alhartomi, S. V. Shvetsova, R. Sahal, and A. Hawbani, "Computing in the sky: A survey on intelligent ubiquitous computing for uav-assisted 6g networks and industry 4.0/5.0," *Drones*, vol. 6, no. 7, p. 177, Jul. 2022.

[41] Q. Hu, Y. Cai, G. Yu, Z. Qin, M. Zhao, and G. Y. Li, "Joint offloading and trajectory design for UAV-enabled mobile edge computing systems," *IEEE Internet of Things Journal*, vol. 6, no. 2, pp. 1879–1892, Oct. 2018.

8. 被引论文：Multi-UAV and SAR collaboration model for disaster management in B5G networks

引用文献：

[1] Chengyi Qu, Francesco Betti Sorbelli, Rounak Singh, Prasad Calyam, Sajal K. Das, "Environmentally-Aware and Energy-Efficient Multi-Drone Coordination and Networking for Disaster Response," in IEEE Transactions on Network and Service Management, vol. 20, no. 2, pp. 1093-1109, June 2023, doi: 10.1109/TNSM.2023.3243543.

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引用部分：

solve a problem on quickly and efficiently collecting messages for all refugees dispersed in shelters after disasters occur. Our proposed communication and networking scheme can be used in works such as [25], [26] and help with achieving drones' monitoring function in order to provide situational awareness for rapid and effective decision making to handle DRM. Although reliable communication architectures have been studied in [27], [28] in the context of drones, they do not address the underlying multi-drone coordination and networking aspects that are necessary to deploy DRM applications.

Another usage of drones in DRM scenarios are related to the potential of extending the communication under situations when network failure occurs or there is intermittent network connectivity. Authors in [29] present an optimal model for computing the trajectories of the drones while guaranteeing the total coverage of the ground mobile sensors and connectivity among the drones with a central base station dedicated to data forwarding strategies described in both proactive or reactive-based protocols. Other solutions that consider only the network traffic congestion based on GPSR utilizing multi-drone orchestrations have been presented in [38], [39], [40]. In these studies, constraints such as wind, and drone's battery are not fully considered in the objective function. Our proposed approach takes environmental features (i.e., wind, obstacles) into account providing solutions at earlier stages (i.e., pre-flight) so that traffic congestion issues do not frequently occur during the establishment of the network links.

The effect of the wind with regards to the A2G communications between drones has been investigated in [41]. Specifically, they study how multiple drones can be effectively used for providing wireless service to ground users. Given the locations of drones, they must expend a control time to adjust their positions dynamically so as to serve multiple users. To minimize this control time, the speed of rotors is optimally adjusted based on both the destinations of the drones and

参考文献：

[39] Y.-N. Chen, N.-Q. Lyu, G.-H. Song, B.-W. Yang, and X.-H. Jiang, "A traffic-aware Q-network enhanced routing protocol based on GPSR for unmanned aerial vehicle ad-hoc networks," *Front. Inf. Technol. Electron. Eng.*, vol. 21, no. 9, pp. 1308–1320, 2020.

[40] A. Saif, K. Dimyati, K. A. Noordin, S. H. Alsamhi, and A. Hawbani, "Multi-UAV and SAR collaboration model for disaster management in B5G networks," *Internet Technol. Lett.*, to be published.

[41] M. Mozaffari, W. Saad, M. Bennis, and M. Debbah, "Communications and control for wireless drone-based antenna array," *IEEE Trans. Commun.*, vol. 67, no. 1, pp. 820–834, Jan. 2019.

[42] G. Bielsa, M. Mezzavilla, J. Widmer, and S. Rangan, "Performance assessment of off-the-shelf mmWave radios for drone communications," in *Proc. Symp. World Wireless, Mobile Multimedia Netw.*, 2019, pp. 1–3.

[43] T. Akram, M. Awais, R. Naqvi, A. Ahmed, and M. Naeem, "Multicriteria UAV base stations placement for disaster management," *IEEE Syst. J.*, vol. 14, no. 3, pp. 3475–3482, Sep. 2020.

[44] H. Trinh et al., "Energy-aware mobile edge computing and routing for low-latency visual data processing," *IEEE Trans. Multimedia*, vol. 20, no. 10, pp. 2562–2577, Oct. 2018.

routing," in *Proc. 2nd IEEE Workshop Mobile Comput. Syst. Appl.*, 1999, pp. 90–100.

[63] G. R. Hiertz et al., "IEEE 802.11s: The WLAN mesh standard," *IEEE Wireless Commun.*, vol. 17, no. 1, pp. 104–111, Feb. 2010.

[64] J. Peng, P. Zhang, L. Zheng, and J. Tan, "UAV positioning based on multi-sensor fusion," *IEEE Access*, vol. 8, pp. 34455–34467, 2020.

[65] D. Tamagawa, E. Taniguchi, and T. Yamada, "Evaluating city logistics measures using a multi-agent model," *Procedia-Social Behav. Sci.*, vol. 2, no. 3, pp. 6002–6012, 2010.

[66] A. Langley et al., "The QUIC transport protocol: Design and Internet-scale deployment," in *Proc. Conf. ACM Special Interest Group Data Commun.*, 2017, pp. 183–196.

[67] M. Seufert, R. Schatz, N. Wehner, and P. Casas, "Quicker or not? An empirical analysis of QUIC vs TCP for video streaming QoE provisioning," in *Proc. 22nd Conf. Innov. Clouds, Internet Netw. Workshops (ICIN)*, 2019, pp. 7–12.

[68] J. Thomson, E. D'Asaro, M. Cronin, W. Rogers, R. Harcourt, and A. Shcherbina, "Waves and the equilibrium range at ocean weather station P," *J. Geophys. Res. Oceans*, vol. 118, no. 11, pp. 5951–5962, 2013.

[2] Chuan-Chi Lai, Bhola, Ang-Hsun Tsai, Li-Chun Wang, "Adaptive and Fair Deployment Approach to Balance Offload Traffic in Multi-UAV Cellular Networks," in IEEE Transactions on Vehicular Technology, vol. 72, no. 3, pp. 3724-3738, March 2023, doi: 10.1109/TVT.2022.3221557.

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引用部分：

I. INTRODUCTION

THE unmanned aerial vehicle base station (UAV-BS) has recently attracted significant attention. It has many unexplored applications and could be a promising solution for current and future wireless communication systems. UAV-BS has some significant advantages over the terrestrial/ground base station than GBS, which guarantees better quality of service (QoS) for ground users [7], [8].

Although a single UAV base station shows advantages in improving wireless network performance, this is still limited by size, weight, power consumption (SWaP), and limited computing power, which directly affects the maximum flight altitude, communication coverage, service endurance [6], and capacity [9]. Thus, the service capacity (maximum number of associated users) of each UAV-BS is limited and may not guarantee availability during the entire mission. A swarm UAV-BS network can provide a longer transmission range, complete missions faster at a lower cost, and achieve more balanced management of traffic offloading than a single UAV-BS network [10]. Therefore, we conclude that the swarm of the UAV-BS network is suitable for many applications, such as in the temporary or sudden surge of bursty communication scenarios, like disaster search and rescue operations [11], [12], live concerts, and traffic overload [13]. Thus, we are motivated to use a swarm of UAV-BSs in this work.

Additionally, user mobility may cause uneven user density at different times and locations, resulting in frequent overloading of UAV-BSs. The number of available of UAV-BSs and user association capacity of a UAV-BS are limited. Under the above constraints, the basic requirement of QoS is that the uneven distribution of users should not affect ongoing user calls. If users are unevenly distributed, QoS will be degraded [14], users will not be able to obtain fair Internet access and meet the latency

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参考文献：

[6] S. Sekander, H. Tabassum, and E. Hossain, "Multi-tier drone architecture for 5G/B5G cellular networks: Challenges, trends, and prospects," *IEEE Commun. Mag.*, vol. 56, no. 3, pp. 96–103, Mar. 2018.

[7] R. Chen, Y. Sun, L. Liang, and W. Cheng, "Joint power allocation and placement scheme for UAV-assisted IoT with QoS guarantee," *IEEE Trans. Veh. Technol.*, vol. 71, no. 1, pp. 1066–1071, Jan. 2022.

[8] Y. Li, S. Xu, Y. Wu, and D. Li, "Network energy efficiency maximization in UAV-enabled air-ground integrated deployment," *IEEE Internet Things J.*, vol. 9, no. 15, pp. 13209–13222, Aug. 2022.

[9] W. Xu et al., "Throughput maximization of UAV networks," *IEEE/ACM Trans. Netw.*, vol. 30, no. 2, pp. 881–895, Apr. 2022.

[10] L. Gupta, R. Jain, and G. Vaszkun, "Survey of important issues in UAV communication networks," *IEEE Commun. Surv. Tut.*, vol. 18, no. 2, pp. 1123–1152, Apr.–Jun. 2016.

[11] A. Saif, K. Dimyati, K. A. Noordin, S. Alsamhi, and A. Haubani, "Multi-UAV and SAR collaboration model for disaster management in B5G networks," *Internet Technol. Lett.*, 2021, Art. no. e310.

[12] M. Deruyck, J. Wyckmans, L. Martens, and W. Joseph, "Emergency ad-hoc networks by using drone mounted base stations for a disaster scenario," in *Proc. IEEE 12th Int. Conf. Wireless Mobile Comput., Netw. Commun.*, New York, NY, USA, 2016, pp. 1–7.

[13] I. Bor-Yaliniz and H. Yanikomeroglu, "The new frontier in RAN heterogeneity: Multi-tier drone-cells," *IEEE Commun. Mag.*, vol. 54, no. 11, pp. 48–55, Nov. 2016.

aerial base stations for traffic offloading and network recovery," *Comput. Netw.*, vol. 156, pp. 52–61, 2019.

[31] A. Akarsu and T. Girici, "Fairness aware multiple drone base station deployment," *IET Commun.*, vol. 12, no. 4, pp. 425–431, 2018.

[32] C. H. Liu, Z. Chen, J. Tang, J. Xu, and C. Piao, "Energy-efficient UAV control for effective and fair communication coverage: A deep reinforcement learning approach," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 9, pp. 2059–2070, Sep. 2018.

[33] H. Huang and A. V. Savkin, "Deployment of heterogeneous UAV base stations for optimal quality of coverage," *IEEE Internet Things J.*, vol. 9, no. 17, pp. 16429–16437, Sep. 2022.

[34] S. Shakoor, Z. Kaleem, D.-T. Do, O. A. Dobre, and A. Jamalipour, "Joint optimization of uav 3-D placement and path-loss factor for energy-efficient maximal coverage," *IEEE Internet Things J.*, vol. 8, no. 12, pp. 9776–9786, Jun. 2021.

[35] B. Galkin, J. Kibilda, and L. A. DaSilva, "Deployment of UAV-mounted access points according to spatial user locations in two-tier cellular networks," in *Proc. Wireless Days*, Toulouse, France, 2016, pp. 1–6.

[36] M. R. Akdeniz et al., "Millimeter wave channel modeling and cellular capacity evaluation," *IEEE J. Sel. Areas Commun.*, vol. 32, no. 6, pp. 1164–1179, Jun. 2014.

[37] U. Demir, M. Ç. İpek, C. Toker, and Ö. Ekici, "Energy-efficient rotary-wing UAV deployment under flight dynamics and QoS constraints," in *Proc. IEEE Int. Black Sea Conf. Commun. Netw.*, Sochi, Russia, 2019, pp. 1–5.

9.被引论文：Green IoT for eco-friendly and sustainable smart cities: future directions and opportunities

引用文献：

[1] Sahal, Radhya, et al. "Blockchain-empowered digital twins collaboration: Smart transportation use case." Machines 9.9 (2021): 193.

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technology for heterogeneous multi-robot collaboration to combat COVID-19 in decentralized peer-to-peer networks without human intervention. Furthermore, the authors of [30] applied blockchain for decentralized multi-drone collaboration to combat COVID -19 in delivering goods and monitoring people in the quarantine area. Furthermore, the authors [19] introduced a machine learning technique for multi-robot collaboration based on keeping connectivity, maintaining the quality of services, and improving mobility during task performances. In [22] addressed drones and IoT devices collaboration to improving greener and smarter cities, while the drones and IoT collaboration resulting green IoT [31,32]. However, no one of the above studies addresses DTs collaboration and applications. Therefore, we discuss DTs collaboration for improving transportation and logistics applications.

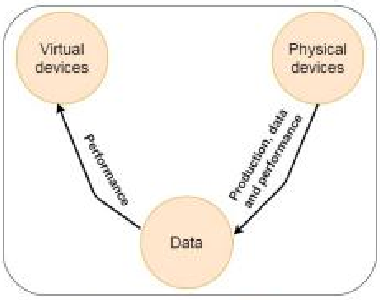

Figure 3. The main parts of DTs [18].

参考文献：

20. Alsamhi, S.H.; Ma, O.; Ansari, M.S. Survey on artificial intelligence based techniques for emerging robotic communication. *Telecommun. Syst.* **2019**, *72*, 483–503. [CrossRef]
21. Alsamhi, S.H.; Ma, O.; Ansari, M.S.; Almalki, F.A. Survey on collaborative smart drones and internet of things for improving smartness of smart cities. *IEEE Access* **2019**, *7*, 128125–128152. [CrossRef]
22. Alsamhi, S.H.; Ma, O.; Ansari, M.S.; Gupta, S.K. Collaboration of drone and internet of public safety things in smart cities: An overview of qos and network performance optimization. *Drones* **2019**, *3*, 13. [CrossRef]
23. Gupta, A.; Sundhan, S.; Gupta, S.K.; Alsamhi, S.H.; Rashid, M. Collaboration of UAV and HetNet for better QoS: A comparative study. *Int. J. Veh. Inf. Commun. Syst.* **2020**, *5*, 309–333. [CrossRef]
24. Li, Q.; Gravina, R.; Li, Y.; Alsamhi, S.H.; Sun, F.; Fortino, G. Multi-user activity recognition: Challenges and opportunities. *Inf. Fusion* **2020**, *63*, 121–135. [CrossRef]
25. Wang, T.; Li, J.; Kong, Z.; Liu, X.; Snoussi, H.; Lv, H. Digital twin improved via visual question answering for vision-language interactive mode in human–machine collaboration. *J. Manuf. Syst.* **2020**, *58*, 261–269. [CrossRef]
26. Andreassen, T.W.; Lervik-Olsen, L.; Snyder, H.; Van Riel, A.C.R.; Sweeney, J.C.; Van Vaerenbergh, Y. Business model innovation and value-creation: The triadic way. *J. Serv. Manag.* **2018**, *29*, 883–906. [CrossRef]
27. De Reuver, M.; Sørensen, C.; Basole, R.C. The digital platform: A research agenda. *J. Inf. Technol.* **2018**, *33*, 124–135. [CrossRef]
28. Eloranta, V.; Orkoneva, L.; Hakanen, E.; Turunen, T. Using platforms to pursue strategic opportunities in service-driven manufacturing. *Serv. Sci.* **2016**, *8*, 344–357. [CrossRef]
29. Alsamhi, S.H.; Lee, B. Blockchain for Multi-Robot Collaboration to Combat COVID-19 and Future Pandemics. *arXiv* **2020**, arXiv:2010.02137.
30. Alsamhi, S.H.; Lee, B.; Guizani, M.; Kumar, N.; Qiao, Y.; Liu, X. Blockchain for decentralized multi-drone to combat COVID-19 and future pandemics: Framework and proposed solutions. *Trans. Emerg. Telecommun. Technol.* **2021**, e4255. [CrossRef]
31. Alsamhi, S.H.; Afghah, F.; Sahal, R.; Hawbani, A.; Al-qaness, A.A.; Lee, B.; Guizani, M. Green Internet of Things using UAVs in B5G Networks: A Review of Applications and Strategies. *Ad Hoc Netw.* **2021**, *117*, 102505. [CrossRef]
32. Almalki, F.; Alsamhi, S.; Sahal, R.; Hassan, J.; Hawbani, A.; Rajput, N.; Saif, A.; Morgan, J.; Breslin, J.; et al. Green IoT for Eco-Friendly and Sustainable Smart Cities: Future Directions and Opportunities. *Mob. Netw. Appl.* **2021**, 1–25.
33. Catarci, T.; Firmani, D.; Leotta, F.; Mandreoli, F.; Mecella, M.; Sapio, F. A Conceptual Architecture and Model for Smart Manufacturing Relying on Service-Based Digital Twins. In Proceedings of the2019 IEEE International Conference on Web Services (ICWS), Milan, Italy, 8–13 July 2019; pp. 229–236.
34. Qi, Q.; Tao, F. Digital twin and big data towards smart manufacturing and industry 4.0: 360 degree comparison. *IEEE Access* **2018**, *6*, 3585–3593. [CrossRef]
35. Qi, Q.; Tao, F.; Hu, T.; Anwer, N.; Liu, A.; Wei, Y.; Wang, L.; Nee, A.Y.C. Enabling technologies and tools for digital twin. *J. Manuf. Syst.* **2019**, 58, 3–21. [CrossRef]

[2] Alsamhi, Saeed Hamood, et al. "Drones' edge intelligence over smart environments in B5G: Blockchain and federated learning synergy." IEEE Transactions on Green Communications and Networking 6.1 (2021): 295-312.

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Things (IoT) in many smart environments leads to maturity with heterogeneous and widespread smart devices improving people's daily life quality. However, the increasing number of distributed smart IoT devices in smart environments cause several challenges in terms of data processing, storage, and transfer which demands considerable computation resources, energy, and radio bandwidth [1]. Intelligence can address some of these challenges by bringing Artificial Intelligence (AI) closer to smart environments [2], [3] that can offer critical demands of smart environments in terms of connectivity, security, and real-time analysis, energy efficiency, etc. Drones can be used as a relay station (mobile drone edge intelligence) to gather data from low-power short-range IoT devices in smart environments, and enhance energy efficiency. Unique features such as easy deployment, 3D mobility, and a higher chance of line-of-sight communication have made drones an essential technology for network coverage extension, enhancing the Quality of Service (QoS) of smart IoT devices while moving the computation capabilities closer to these devices [4]–[6]. Due to the above benefits, drones can offer a promising solution for various B5G applications in smart environments [7]–[14], where the drone can be utilized as an intelligent edge node to assist in data gathering, provide efficient computing capability, and train data models locally [15]. Therefore, drones make environments smarter and greener [8]. However, drone-aided IoT in smart environments faces security and energy challenges. Limited energy leads to a limited network access lifetime. Fig. 1 shows few used cases of using drones in smart environments with the help of B5G technologies.

参考文献：

intelligence over smart environments is required to meet the enormous demand of a range of terrestrial consumers. Furthermore, to provide a service as a whole, numerous drone edge intelligence should be intelligently controlled. The use of multiple-agent RL for intelligent control of numerous drones is both intriguing and challenging [15].

FL Drone in B5G: B5G provides a unique communication architecture for autonomous vehicle systems to execute complex smart applications. Drones may be used as relay devices to convey communications and assist edge servers because they fly near the smart devices or the end-users. Furthermore, using FL techniques, drones may assist in processing the acquired data and sending the learned model to ground station, where all of the received models are pooled and compared for decision making. However, adopting FL integrated drone technology places additional constraints on computation, necessitating optimising drone resources based on efficient task allocation, scheduling, and various other mechanisms to reduce energy consumption and extend operation lifetime.

Storage Off-Chain: Drones trade a variety of data. Some of the data may be too huge to fit into the blockchain properly, or it may need to be modified or deleted often. To solve this issue and improve speed, off-chain blockchain storage should be made available.

Designing Framework for Energy Efficiency Analysis: The combination of FL and blockchain to design an efficient framework for energy efficiency analysis is needed to be addressed and discussed more with highlighting the benefits of the combination. Furthermore, efficient protocols are also needed for improving energy efficiency, maintaining QoS and enhancing

REFERENCES

[1] B. Heintz, A. Chandra, and R. K. Sitaraman, "Optimizing grouped aggregation in geo-distributed streaming analytics," in *Proc. 24th Int. Symp. High-Perform. Parallel Distrib. Comput.*, 2015, pp. 133–144.

[2] E. Li, Z. Zhou, and X. Chen, "Edge intelligence: On-demand deep learning model co-inference with device-edge synergy," in *Proc. Workshop Mobile Edge Commun.*, 2018, pp. 31–36.

[3] Z. Zhou, X. Chen, E. Li, L. Zeng, K. Luo, and J. Zhang, "Edge intelligence: Paving the last mile of artificial intelligence with edge computing," *Proc. IEEE*, vol. 107, no. 8, pp. 1738–1762, Aug. 2019.

[4] B. Li, Z. Fei, and Y. Zhang, "UAV communications for 5G and beyond: Recent advances and future trends," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 2241–2263, Apr. 2019.

[5] F. Afghah, A. Razi, J. Chakareski, and J. Ashdown, "Wildfire monitoring in remote areas using autonomous unmanned aerial vehicles," in *Proc. IEEE INFOCOM Conf. Comput. Commun. Workshops (INFOCOM WKSHPS)*, 2019, pp. 835–840.

[6] A. Shamsoshoara, F. Afghah, E. Blasch, J. Ashdown, and M. Bennis, "UAV-assisted communication in remote disaster areas using imitation learning," *IEEE Open J. Commun. Soc.*, vol. 2, pp. 738–753, Mar. 2021.

[7] F. A. Almalki *et al.*, "Green IoT for eco-friendly and sustainable smart cities: Future directions and opportunities," *Mobile Netw. Appl.*, pp. 1–25, Aug. 2021, doi: 10.1007/s11036-021-01790-w.

[8] S. H. Alsamhi *et al.*, "Green Internet of Things using UAVs in B5G networks: A review of applications and strategies," *Ad Hoc Netw.*, vol. 117, Jun. 2021, Art. no. 102505.

[9] S. H. Alsamhi *et al.*, "Machine learning for smart environments in B5G networks: Connectivity and qos," *Comput. Intell. Neurosci.*, vol. 2021, Sep. 2021, Art. no. 6805151.

[10] S. H. Alsamhi, O. Ma, M. S. Ansari, and S. K. Gupta, "Collaboration of drone and Internet of public safety things in smart cities: An overview of QoS and network performance optimization," *Drones*, vol. 3, no. 1, p. 13, 2019.

[11] F. A. Almalki, B. O. Soufiene, S. H. Alsamhi, and H. Sakli, "A low-cost platform for environmental smart farming monitoring system based on IoT and UAVs," *Sustainability*, vol. 13, no. 11, p. 5908, 2021.

10. Routing Schemes in Software-defined Vehicular Networks: Design, Open Issues and Challenges.

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[1] Zhao, Liang, et al. "Intelligent digital twin-based software-defined vehicular networks." IEEE Network 34.5 (2020): 178-184.

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improved routing schemes are verified in the virtual networks in which the scheme with the best performance is selected to be deployed in the physical network. In this context, the same type of errors will be avoided by applying the newly updated routing schemes. In our proposed architecture, there are generally two routing modes of IDT-SDVN, including policy-based IDT-SDVN, and routing-based IDT-SDVN, which will be explained in the following section. Moreover, we will also give the components of the real-world IDT-SDVN and the services of IDT-SDVN.

Routing Modes of IDT-SDVN

Policy-Based IDT-SDVN: In this mode, the controller only distributes the routing policy to each vehicle periodically. Here, the routing policy can be referred to as all types of rule-related information excepting the calculation of flow-tables. These rules can be locally agreed on updating routing metrics [6], switching of routing protocol [5], or other types of intelligence rules. Routing policies can be updated from time to time, according to the results from the virtual network.

Routing-Based IDT-SDVN: In this mode, the flow table is only calculated in the controller. Intelligent algorithms are also promising to provide route calculation with minimum networking overhead. For example, the temporal routing can be applied with the Markov model to calculate the flow-table predictively. In the IDT side, other learning algorithms, such as reinforcement learning, can also be used to upgrade the routing schemes according to the demand of vehicles in the dynamic changing networks where routing schemes can, from the collected information from the vehicles.

devices. To this end, the MEC server can gather all types of data within its dominated area by collecting them from update messages, surrounding sensors [8], and data exchange of different MEC servers and cloud. With further considering the matter of privacy, we can fuse the data as an additional source for enhancing the global view of the SDVN controller and decision making of the controller in a low-cost way. For example, the images and videos collected by the roadside cameras will be transmitted to the MEC server for processing information containing the plane number, and vehicle type can be extracted to help the reduction of the uplink transmission cost from vehicle to the controller. An MEC server has typically limited storage size, which is only applied to save newly collected or lightweight data for instant reading and writing for its local vehicles. The MEC server will transfer the out-of-date data or big pieces of data to the cloud. In this context, the higher-level cloud can also provide a bigger vision of the virtual network for its covered MECs.

IDT-SDVN Services

Data Aggregation and Virtualization: With the global view, each controller can collect and store vehicular and road data within its region. Then, the real-time digital twin of the physical SDVN can be constructed regarding the massive amount of data in the controller and the data processed from the MEC server. In addition, by predicting the future states of vehicles and roads, multiple future virtual SDVNs can be constructed.

IDT Networking: Controller offers higher computational power compared with vehicles which enable intelligent algorithm operated to refine the

参考文献：

Reinforcement Learning is a good candidate for IDT-SDVN in the case of temporal graph routing, which can assist in obtaining better tuning parameters. For example, in the RL version, we can decide the right tuning parameters of prediction methods based on the rewards (simulation outcomes or results) of the virtual SDVNs.

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References

[1] H. Li, M. Dong, and K. Ota, "Control Plane Optimization in Software-Defined Vehicular Ad Hoc Networks," *IEEE Trans. Vehic. Tech.*, vol. 65, no. 10, 2016, pp. 7895–7904.
[2] F. A. Silva *et al.*, "Information-Driven Software-Defined Vehicular Networks: Adapting Flexible Architecture to Various Scenarios," *IEEE VT Mag.*, vol. 14, no. 1, 2019, pp. 98–107.
[3] Y. Gao *et al.*, "A Hierarchical Routing Scheme with Load Balancing in Software Defined Vehicular Ad Hoc Networks," *IEEE Access*, vol. 6, 2018, pp. 73774–85.
[4] F. Tao et al., "Digital Twin in Industry: State-of-the-Art," *IEEE TII*, vol. 15, no. 4, 2019, pp. 2405–15.
[5] L. Zhao *et al.*, "A Novel Adaptive Routing and Switching Scheme for Software-Defined Vehicular Networks," *Proc. IEEE ICC*, 2019.
[6] L. Zhao *et al.*, "Routing Schemes in Software-defined Vehicular Networks: Design, Open Issues and Challenges," *IEEE ITS Mag.*, 2019.
[7] T. Das, V. Sridharan, and M. Gurusamy, "A Survey on Controller Placement in SDN," *IEEE Commun. Surveys & Tutorials*, 2019.
[8] P. Liu et al., "FRCA: A Novel Flexible Routing Computing Approach for Wireless Sensor Networks," *IEEE TMC*, 2019.
[9] L. Zhao *et al.*, "A Temporal-Information-based Adaptive Routing Algorithm for Software Defined Vehicular Networks," *Proc. IEEE ICC 2019*, Shanghai.
[10] R. Jia *et al.*, "Data Driven Congestion Trends Prediction of Urban Transportation," *IEEE Internet Things J.*, vol. 5, no. 2, 2018, pp. 581–91.
[11] G. Han *et al.*, "An Uneven Cluster-Based Mobile Charging Algorithm for Wireless Rechargeable Sensor Networks," *IEEE Systems J.*, 2018.
[12] G. Han et al., "A Multicharger Cooperative Energy Provision Algorithm Based on Density Clustering in the Industrial Internet of Things," *IEEE Internet Things J.*, vol. 6, no. 5, 2019, pp. 9165–74.
[13] S. H. Alsamhi *et al.*, "Greening Internet of Things for Smart Everything with a Green-Environment Life: A Survey and Future Perspectives," *Telecommun. Systems*, 2019.
[14] W. Miao *et al.*, "Stochastic Performance Analysis of Network Function Virtualisation in Future Internet," *IEEE JSAC*, vol. 37, no. 3, 2019, pp. 613–26.
[15] J. Wu *et al.*, "A Multi-UAV Clustering Strategy for Reducing Insecure Communication Range," COMNET, vol. 158, 2019, pp. 132–42.

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[2] Zhao, Liang, et al. "A novel generation-adversarial-network-based vehicle trajectory prediction method for intelligent vehicular networks." IEEE Internet of Things Journal 8.3 (2020): 2066-2077.

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引用部分：

Abstract—**Prediction of the future location of vehicles and other mobile targets is instrumental in intelligent transportation system applications. In fact, networking schemes and protocols based on machine learning can benefit from the results of such accurate trajectory predictions. This is because routing decisions always need to be made for the future scenario due to the inevitable latency caused by the processing and propagation of the routing request and response. Thus, to predict the high-precision trajectory beyond the state of the art, we propose a generative adversarial network (GAN)-based vehicle trajectory prediction method, GAN-VEEP, for urban roads. The proposed method consists of three components: 1) vehicle coordinate transformation for data set preparation; 2) neural network prediction model trained by GAN; and 3) vehicle turning model to adjust the prediction process. The vehicle coordinate transformation model is introduced to deal with the complex spatial dependence in the urban road topology. Then, the neural network prediction model learns from the behavior of vehicle drivers. Finally, the vehicle turning model can refine the driving path based on the driver's psychology. Compared with its counterparts, the experimental results show that GAN-VEEP exhibits higher effectiveness in terms of the average accuracy, mean absolute error, and root-mean-squared error.**

Index Terms—**Behavior model of vehicle drivers, generative adversarial network (GAN), spatial dependence, vehicle trajectory prediction.**

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I. Introduction

WITH the development of the intelligent transportation systems (ITSs), the demand for various applications that are dependent on vehicle trajectory continues to expand, such as travel planning, urban traffic congestion mitigation, and urban traffic management. Vehicular networking is the key enabler for ITS applications that are onboard and which are expected to be utilized to collect vehicular data in real time. Besides, a variety of services for passengers and drivers can be made possible by onboard applications, such as vehicle road safety and travel experience and efficiency. Although vehicular networking has attracted a lot of attention from both academia and industry, current forms of networking schemes still suffer from the impassable ceiling of QoS parameters. This is partly because the simulation and design of these schemes are mostly based on historical data [1]. An extreme case is packet routing for highly dynamic vehicles. The routing decision is made to respond to an early time request while the route is for guiding data messages in the future network. This does exist in all types of mobile multihop networks. However, it can cause the most serve problem in vehicular networks as it is of vital importance for driving applications to exchange data with minimum latency and data drops. On the other hand, when it comes to discussing the next-generation vehicular networks, learning new routing schemes is an inevitable ability. Although the software-defined vehicular network (SDVN) is a feasible networking paradigm for learning, the existing data to feed the machine are still historical, where the road information is collected at an earlier time due to the transmission delay [2].

参考文献：

performance in position and speed prediction, which proves the effectiveness of the model in short-term vehicle trajectory prediction tasks. In Fig. 9(b), Maneuver, DNN, and TrajclusiVAT reach the peak and then begin to decline. This is because some vehicles end their journey after arriving at the destination. Here, since the speed of vehicles in Maneuver is the highest, the model also reaches the peak as the earliest method. The overall trend of speed error and distance error is similar, which shows that the position of the vehicle is closely related to the speed of the vehicle. The speed of the vehicle affects the accuracy of the whole track by affecting the position of the vehicle. To conclude, the most accurate model for vehicle speed modeling can often obtain the most accurate prediction trajectory. GAN-VEEP, therefore, can get better prediction results by learning the hidden behavior of vehicle drivers from the historical data.

Finally, we verify the robustness of GAN-VEEP to test noise immunity through perturbation analysis experiments. Two types of common random noise are added to the data set. They obey Gaussian distribution $N(0, \sigma^2)$, where $\sigma \in (0.2, 0.4, 0.8, 1, 2)$, and Poisson distribution $P(y)$, and $y \in (0.2, 0.4, 0.8, 1, 2)$, respectively. To illustrate the robustness of our proposal, we evaluate the stability of GAN-VEEP in terms of traffic speed and traffic flow. The results are shown as follows. Fig. 10(a) and (b) shows the results of the traffic speed after adding Gaussian noise and Poisson noise, respectively, where the vertical axis represents the change of each evaluation metrics, and different colors indicate different metrics. Similarly, Fig. 10(c) and (b) is the results of the traffic flow after adding Gaussian noise and Poisson noise, respectively. From the above results, it can be seen that the fluctuations of metrics are relatively small whatever the noise distribution is.

VII. Conclusion

In this article, a novel short-term high-precision vehicle trajectory prediction method, GAN-VEEP is proposed. First, we used a vehicle coordinate normalization model to transform the position coordinates of each vehicle into *normalized coordinates*. This method improves the accuracy of the prediction model for vehicle trajectory prediction. Then, we used GAN to train a high-precision vehicle position prediction model to forecast the driving position of the vehicle on the current RSG. A cost-based vehicle turning model is introduced to select the next driving direction when the vehicle turns. According to the experimental results, compared with existing methods, GAN-VEEP has shown excellent performance in predicting vehicle trajectory on urban road scenarios.

References

[1] W. Quan, N. Cheng, P. Jing, G. Liu, and X. S. Shen, "VeData: Promoting AI assisted autonomous vehicles," in *Proc. MOBICOM*, 2018, pp. 771–773.
[2] L. Zhao, A. Al-Dubai, A. Y. Zomaya, G. Min, A. Hawbani, and J. Li, "Routing schemes in software-defined vehicular networks: Design, open issues and challenges," *IEEE Intell. Transp. Syst. Mag.*, early access.
[3] D. Zhao, Y. Gao, Z. Zhang, Y. Zhang, and T. Luo, "Prediction of vehicle motion based on Markov model," in *Proc. ICCSEC*, Dec. 2017, pp. 205–209.
[4] S. D. Oh, Y. J. Kim, and J. S. Hong, "Urban traffic flow prediction system using a multifactor pattern recognition model," *IEEE Trans. Intell. Transp. Syst.*, vol. 16, no. 5, pp. 2744–2755, Oct. 2015.
[5] Z. Bartlett, L. Han, T. T. Nguyen, and P. Johnson, "A machine learning based approach for the prediction of road traffic flow on urbanised arterial roads," in *Proc. HPCC/SmartCity/DSS*, Jun. 2018, pp. 1285–1292.
[6] W. Xiao, J. Zou, H. Li, and K. Xu, "Smooth trajectory tracking using longitudinal distance constraint for a 4WS4WD unmanned ground vehicle," in *Proc. IEEE Int. Conf. Robot. Biomimetics (ROBIO)*, Dec. 2019, pp. 2105–2110.
[7] Y. Chen, C. Hu, and J. Wang, "Human-centered trajectory tracking control for autonomous vehicles with driver cut-in behavior prediction," *IEEE Trans. Veh. Technol.*, vol. 68, no. 9, pp. 8461–8471, Sep. 2019.

[3] Li, Zhuhui, et al. "Reliable and Scalable Routing Under Hybrid SDVN Architecture: A Graph Learning Based Method." IEEE Transactions on Intelligent Transportation Systems (2023).

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to enlarger one vehicle's vision and analyse capability with simple liner computation requirements. However, the training for the NiGCN model is difficult for an individual vehicle due to its limited computation resource and scarce training data. Thus, we want to introduce SDVN architecture. The separation of the data plane and the control plane is the core idea of SDVNs [12], [13]. Since the control plane in SDVNs collects the information of vehicles periodically, it senses the vehicular network globally [14]. Typically, the control plane computes all requested routing paths from the data plane centralised in SDVN architectures. These centralised management methods inevitably increase the communication and computation overhead, and high mobility of vehicles and possible packet loss make the connectivity between control and data plane unstable [15]. Thus, we ease the communication and computation burden for the control plane by assigning the control plane with the decision model training task, and the data plane (vehicles) makes the relay decision independently based on the centralised trained decision model. This hybrid SDVN architecture significantly reduces the communication between the control and data plane. Single point failure can be avoided, and stability and scalability of the network management can be well improved.

To this end, based on the NiGCN model and hybrid SDVN architecture, we propose a novel routing algorithm, namely, a novel NiGCN-based greedy routing algorithm (NGGRA) for hybrid SDVNs. As a premise, all vehicles can exchange

brid SDVN architecture, the proposed routing algorithm guarantees the global view while reducing the network overhead.

The rest of the paper is organised as follows. Section II introduces the hybrid SDVN architecture and presents problem formulation. Our novel NiGCN model is described in detail in Section III. Section IV presents our routing algorithm architecture, NGGRA. In Section V, the simulation results on NiGCN and NGGRA are presented and analysed from different perspectives. Finally, Finally, the conclusion is drawn out in Section VI.

II. Network Model and Problem Formulation

Section II.A. describes the network model. The problem formulation of this work and the solution will be presented in Section II.B.

A. Hybrid SDVN

In the traditional SDVNs, the control plane collects the information of vehicles periodically to sense the vehicular network globally [14] as assistance for routing decisions. However, the centralised architecture is vulnerable to the single-point failure [17]. It will also increase network overhead due to the frequent information exchange between data and the control plane, which is an inherent disadvantage compared to the distributed architecture [15].

参考文献：

networks in city environments," in *Proc. 3rd Int. workshop Veh. Ad Hoc Netw.*, Sep. 2006, pp. 88–89.

[11] Z. Zhang, P. Cui, and W. Zhu, "Deep learning on graphs: A survey," *IEEE Trans. Knowl. Data Eng.*, vol. 34, no. 1, pp. 249–270, Jan. 2022.

[12] D. Kreutz, F. M. V. Ramos, P. E. Veríssimo, C. E. Rothenberg, S. Azodolmolky, and S. Uhlig, "Software-defined networking: A comprehensive survey," *Proc. IEEE*, vol. 103, no. 1, pp. 14–76, Jan. 2015.

[13] L. Zhao, K. Yang, Z. Tan, X. Li, S. Sharma, and Z. Liu, "A novel cost optimization strategy for SDN-enabled UAV-assisted vehicular computation offloading," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 6, pp. 3664–3674, Jun. 2021.

[14] L. Zhao, J. Li, A. Al-Dubai, A. Y. Zomaya, G. Min, and A. Hawbani, "Routing schemes in software-defined vehicular networks: Design, open issues and challenges," *IEEE Intell. Transp. Syst. Mag.*, vol. 13, no. 4, pp. 217–226, Mar. 2020.

[15] M. M. Islam, M. T. R. Khan, M. M. Saad, and D. Kim, "Software-defined vehicular network (SDVN): A survey on architecture and routing," *J. Syst. Archit.*, vol. 114, Mar. 2021, Art. no. 101961. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1383762120302113

[16] A. Akhunzada and M. K. Khan, "Toward secure software defined vehicular networks: Taxonomy, requirements, and open issues," *IEEE Commun. Mag.*, vol. 55, no. 7, pp. 110–118, Jul. 2017.

[34] L. Zhao and A. Y. Al-Dubai, "Routing metrics for wireless mesh networks: A survey," in *Recent Advances in Computer Science and Information Engineering*. Cham, Switzerland: Springer, 2012, pp. 311–316.

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[4] Boukerche, Azzedine, and Noura Aljeri. "An energy-efficient controller management scheme for software-defined vehicular networks." IEEE Transactions on Sustainable Computing 7.1 (2021): 61-74.

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引用部分：

forwarding and re-routing ongoing sessions must be handled by the control unit to prevent lengthy delays in communications and disruption of packet delivery. In addition, the increased number of vehicles on the road and the increased load and cost of connectivity of the controller unit create a bottleneck issue in the design of SDN-enabled vehicular networks.

The problem of large-scale and dense networks in the implementation of SDN-based vehicular networks has been studied in the literature [8]. The control layer is made up of several controllers in a distributed or hierarchical design [9]. Each controller is responsible for a group of switches on the network. This guarantees a flexible network architecture that manages a high level of overhead traffic. In line with this principle, many questions are raised about the structure of distributed SDN-based vehicular networks (D-SDVN), including the optimum number of controllers that can be allocated to a given network configuration, the switch clustering strategy [10], and how the implementation adapts to the vehicles' rapid mobility.

This work proposes an energy-efficient adaptive mobility-based SDN controller assignment and selection strategy for software-defined vehicular networks based on the heterogeneous communication between switches and vehicle mobility at a given area and time. This work aims to reduce the overall network latency through the proper deployment of the switch/controller topology, which fits best the vehicle's density. Moreover, we propose a new split-and-merge strategy to adaptively reduce/add controllers to the network to balance the load in each cluster and reduce the energy consumption of switch-migration. We derive the preliminaries and problem statement to build a system model, followed by a detailed description of the proposed clustering method and an empirical evaluation of the proposed method compared to several

2 Background

In this section, an overview of software-defined vehicular networks is presented and a discussion of the recent literature studies that address the controller deployment and selection problem in vehicular networks.

2.1 Distributed SDN-Based Vehicular Networks

The design of a centralized SDN controller poses several challenges in ultra-dense networks and, in particular, in the continuously changing network topology, rapid vehicles' mobility [11], opportunistic routing protocols [12], [13]. Also, a centralized controller introduces a single point of failure issue, in which the failure of that controller leads to an increased delay in packet delivery and data drop rate. Such a situation can be disastrous for time-sensitive traffic and safety applications/services such as emergency warnings, autonomous driving, and environmental monitoring. Also, with the tremendous growth in the number of vehicles, base stations, and ubiquitous IoT devices, having one controller may not handle the rise of data flow. This is because various applications/services expect a minimum duration of delay by the controller to set up a route, especially in a dynamically mobile environment. Finally, when we deal with vehicles' rapid mobility, the frequent changes in points of access often involve controller interaction to keep track of the vehicles' mobility and locations. Therefore, there is going to be a significant overhead on the network. As a result, several research studies addressed the problem by introducing other alternative designs to SDN-enabled vehicular networks by using either the hierarchical [10], distributed [14], or the Edge-and Cloud-Computing model [15]. Thus, reducing the load on the centralized unit and eliminating the single point of failure problem.

参考文献：

the AP techniques, as seen in Fig. 14b, an average change of 6 and 3 in MSE and DBI respectively, while the split and merge method showed only an average of 1 change in controller position or mode (i.e., On/Off). Hence, the high reduction in the migration cost in the split and merge method comes as an advantage to the overall network performance, especially if we consider a dense network design with abundant set of switch-enabled RSUs.

5 Conclusion

The distributed software-defined vehicular network design faces several challenges, including vehicles' high mobility and changes in network densities. One crucial issue in D-SDVN is the controller deployment and management problem, which significantly impacts the network's overall performance. This article presented an adaptive controller deployment and management scheme based on the vehicles' traffic-flow information and an adaptive split and merge clustering technique. We have studied the connectivity link measurement between different vehicular network entities and provided a scalable approach to place controllers and assign switches to them dynamically. We combine a modified incremental k-mean clustering method with a split and merge technique to minimize the selected objective function. A thorough performance evaluation is conducted and compared to different static and dynamic clustering methods. Our results showed the proposed method's efficiency in terms of end-to-end delay, load on controllers, migration cost, and energy consumption. The

[8] S. Correia, A. Boukerche, and R. I. Meneguette, "An architecture for hierarchical software-defined vehicular networks," *IEEE Commun. Mag.*, vol. 55, no. 7, pp. 80–86, Jul. 2017.

[9] J. Qiao, Y. He, and X. S. Shen, "Improving video streaming quality in 5G enabled vehicular networks," *IEEE Wirel. Commun.*, vol. 25, no. 2, pp. 133–139, Apr. 2018.

[10] K. S. Atwal, A. Guleria, and M. Bassiouni, "SDN-based mobility management and QoS support for vehicular ad-hoc networks," in *Proc. Int. Conf. Comput., Netw. Commun.*, 2018, pp. 659–664.

[11] A. Mahmood, W. E. Zhang, and Q. Z. Sheng, "Software-defined heterogeneous vehicular networking: The architectural design and open challenges," *Future Internet*, vol. 11, no. 3, 2019, Art. no. 70.

[12] L. Zhao, A. Al-Dubai , A. Y. Zomaya, G. Min, A. Hawbani, and J. Li, "Routing schemes in software-defined vehicular networks: Design open issues and challenges," *IEEE Intell. Transp. Syst. Mag.*, early access, Mar. 12, 2020, doi: 10.1109/MITS.2019.2953557.

[13] M. Salehi, A. Boukerche, and A. Darehshoorzadeh, "Modeling and performance evaluation of security attacks on opportunistic routing protocols for multihop wireless networks," *Ad Hoc Netw.*, vol. 50, pp. 88–101, 2016.

[14] C. Qiu, F. R. Yu, F. Xu, H. Yao, and C. Zhao, "Blockchain-based distributed software-defined vehicular networks via deep q-learning," in *Proc. 8th ACM Symp. Des. Anal. Intell. Veh. Netw. Appl.*, 2018, pp. 8–14.

[15] J. Liu, J. Wan, B. Zeng, Q. Wang, H. Song, and M. Qiu, "A scalable and quick-response software defined vehicular network assisted by mobile edge computing," *IEEE Commun. Mag.*, vol. 55, no. 7, pp. 94–100, Jul. 2017.

[16] B. Heller, R. Sherwood, and N. McKeown , "The controller placement problem," in *Proc. 1st Workshop Hot Top. Softw. Defined Netw.*, 2012, pp. 7–12.

[17] Y. Xu *et al.*, "Dynamic switch migration in distributed software-defined networks to achieve controller load balance," *IEEE J. Sel. Areas Commun.*, vol. 37, no. 3, pp. 515–529, Mar. 2019.

[18] G. Wang, Y. Zhao, J. Huang, and W. Wang, "The controller placement problem in software defined networking: A survey," *IEEE Netw.*, vol. 31, no. 5, pp. 21–27, Sep. 2017.

[19] J. Liao, H. Sun, J. Wang, Q. Qi, K. Li, and T. Li, "Density cluster

11. A Novel Deep Q-Learning-Based Air-Assisted Vehicular Caching Scheme for Safe Autonomous Driving

[1] Mao, Bomin, et al. "AI models for green communications towards 6G." IEEE Communications Surveys & Tutorials 24.1 (2021): 210-247.

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引用部分：

and different content combinations are as the reward and state, respectively. To accelerate the convergence of proposed intelligent content caching method, the authors utilize the latest findings including the prioritized experience replay [270], dueling architecture, and deep RNN. Extensive simulations illustrate the proposed intelligent content caching algorithms can significantly improve energy efficiency for both the stationary and dynamic popularity distributions. Reference [271] analyzes impacts of the channel conditions on content caching, where the RL-based content caching is proposed to alleviate energy consumption.

Shi *et al.* [249] adopt the DQN model to optimize the content caching in hierarchical vehicular networks of three layers, where an airship distributes the contents to UAVs for satisfying the terrestrial services. In the considered scenario, the airship needs to dispatch the UAV caching the required contents to provide the service if the requested content is not in local UAV, which means more energy consumption. To minimize energy consumption, the DQN model is proposed and the defined reward considers the probabilities of local UAV requests and other UAV scheduling. To improve training performance, the experience replay mechanism is considered. And the proposed DQN model is verified to overcome the large number of states in the training process.

usage. Then, the updated parameters and extracted features are uploaded to the server, where the hybrid filtering technique is adopted to decide the content caching policy. To further ensure data security, blockchain techniques can be adopted in the data transmission process [273]. However, these research works aim to improve the caching performance instead of the minimization of energy consumption.

2) Content Delivery: Besides content caching, how to deliver the contents is also an important factor to affect energy consumption. In this part, we discuss the related AI-based research on content delivery optimization.

Lei *et al.* [274] study the content caching and delivery in cellular networks, and a supervised DNN-based approach is adopted to optimize the user clustering to minimize the transmit power of BSs. In each cell, the content delivery should satisfy the stringent delay requirement, thus the user scheduling algorithm should have less computation time to enable real-time operations. To realize this goal, the DNN is trained to map from the users' channel coefficients and requested data amount to the clustering scheduling policy. The authors utilize a variable size of dataset generated with conventional iterative algorithms to train the proposed DNN. And the performance shows that the large sized dataset can result in 90% approximation to the optimum with limited time.

参考文献：

[225] J. Zhang, J. Tang, and F. Wang, "Cooperative relay selection for load balancing with mobility in hierarchical WSNs: A multi-armed bandit approach," *IEEE Access*, vol. 8, pp. 18110–18122, 2020.
[226] Z. Zhou, F. Xiong, C. Xu, Y. He, and S. Mumtaz, "Energy-efficient vehicular heterogeneous networks for green cities," *IEEE Trans. Ind. Informat.*, vol. 14, no. 4, pp. 1522–1531, Apr. 2018.
[227] H. Mostafaei, "Energy-efficient algorithm for reliable routing of wireless sensor networks," *IEEE Trans. Ind. Electron.*, vol. 66, no. 7, pp. 5567–5575, Jul. 2019.
[228] X. Wang, T. Jin, L. Hu, and Z. Qian, "Energy-efficient power allocation and Q-learning-based relay selection for relay-aided D2D communication," *IEEE Trans. Veh. Technol.*, vol. 69, no. 6, pp. 6452–6462, Jun. 2020.
[229] K. Haseeb, K. M. Almustafa, Z. Jan, T. Saba, and U. Tariq, "Secure and energy-aware heuristic routing protocol for wireless sensor network," *IEEE Access*, vol. 8, pp. 163962–163974, 2020.
[230] L. Xiao, D. Jiang, Y. Chen, W. Su, and Y. Tang, "Reinforcement-learning-based relay mobility and power allocation for underwater sensor networks against jamming," *IEEE J. Ocean. Eng.*, vol. 45, no. 3, pp. 1148–1156, Jul. 2020.
[231] T. Fu, C. Wang, and N. Cheng, "Deep-learning-based joint optimization
[247] C. Yang, K. Chin, T. He, and Y. Liu, "On sampling time maximization in wireless powered Internet of Things," *IEEE Trans. Green Commun. Netw.*, vol. 3, no. 3, pp. 641–650, Sep. 2019.
[248] J. Yan, S. Bi, and Y. J. A. Zhang, "Offloading and resource allocation with general task graph in mobile edge computing: A deep reinforcement learning approach," *IEEE Trans. Wireless Commun.*, vol. 19, no. 8, pp. 5404–5419, Aug. 2020.
[249] J. Shi, L. Zhao, X. Wang, W. Zhao, A. Hawbani, and M. Huang, "A novel deep Q-learning-based air-assisted vehicular caching scheme for safe autonomous driving," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 7, pp. 4348–4358, Jul. 2021.
[250] J. Tang *et al.*, "Energy minimization in D2D-assisted cache-enabled Internet of Things: A deep reinforcement learning approach," *IEEE Trans. Ind. Informat.*, vol. 16, no. 8, pp. 5412–5423, Aug. 2020.
[251] Q. Li, Y. Sun, Q. Wang, L. Meng, and Y. Zhang, "A green DDPG reinforcement learning-based framework for content caching," in *Proc. 12th Int. Conf. Commun. Softw. Netw. (ICCSN)*, Chongqing, China, Jun. 2020, pp. 223–227.
[252] M. Chen, M. Mozaffari, W. Saad, C. Yin, M. Debbah, and C. S. Hong, "Caching in the sky: Proactive deployment of cache-enabled unmanned aerial vehicles for optimized quality-of-experience," *IEEE J. Sel. Areas

[2] Kurunathan, Harrison, et al. "Machine learning-aided operations and communications of unmanned aerial vehicles: A contemporary survey." IEEE Communications Surveys & Tutorials (2023).

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引用部分：

In [196], cache-enabled UAVs are employed with MEC to assist content placement of the ground nodes. Given the limited battery power of the UAV, a double DQN model is developed for the UAV to maximize the network throughput. Since DQN may overestimate the action-value function, double DQN is utilized in [197] to maximize the long-term network throughput of MEC with the consideration of energy consumption of the UAV and QoS requirements. UAVs can also be used to provide vehicular content caching in MEC-enabled autonomous driving [198]. In this model, the UAV learns various vehicular content and available caching space to enhance the content response performance.

Others: In [199], UAV-assisted wireless power transfer (WPT) is studied with the DQN to design the flight trajectories and improve the energy harvesting efficiency. The the flight time to the destination, and the battery level of the UAV. DDPG can also be used to design the UAV's 3D movement to reduce the energy consumption and enhance the throughput fairness of the ground nodes since a battery-powered UAV has limited flight time [208].

Age of information: In [147], the trajectories of UAVs are designed to collect vehicular data while ensuring a minimized AoI to keep the information fresh. DDPG is used to learn time-varying traffic and road conditions, e.g., the number of ground vehicles, the instantaneous position of ground vehicles, and the AoI of ground vehicles. Based on the learning outcome of the DDPG, the AoI can be minimized by conducting the designed trajectories and scheduling policy. Sun *et al.* [209] studied a twin delayed DDPG (TD3) model to minimize the AoI and energy consumption

参考文献：

pp. 109–121, 2019.

[175] Z. Lu, K. Zhang, J. He, and Y. Niu, "Applying k-means clustering and genetic algorithm for solving mtsp," in *International Conference on Bio-Inspired Computing: Theories and Applications*. Springer, 2016, pp. 278–284.

[176] H. Huang and A. V. Savkin, "An algorithm of reactive collision free 3-D deployment of networked unmanned aerial vehicles for surveillance and monitoring," *IEEE Transactions on Industrial Informatics*, vol. 16, no. 1, pp. 132–140, 2019.

[177] T. F. Villa, F. Salimi, K. Morton, L. Morawska, and F. Gonzalez, "Development and validation of a UAV based system for air pollution measurements," *Sensors*, vol. 16, no. 12, p. 2202, 2016.

[178] H. Niu, D. Wang, and Y. Chen, "Estimating crop coefficients using linear and deep stochastic configuration networks models and UAV-based normalized difference vegetation index (NDVI)," in *2020 International Conference on Unmanned Aircraft Systems (ICUAS)*. IEEE, 2020, pp. 1485–1490.

[179] Y. Kageyama, J. Takahashi, M. Nishida, B. Kobori, and D. Nagamoto, "Analysis of water quality in miharu dam reservoir, Japan, using UAV data," *IEEJ Transactions on Electrical and Electronic Engineering*, vol. 11, pp. S183–S185, 2016.

[180] P. Yao, W. Honglun, and H. Ji, "Gaussian mixture model and receding horizon control for multiple UAV search in complex environment," *Nonlinear Dynamics*, vol. 88, 04 2017.

[181] A. A. R. Newaz, S. Jeong, H. Lee, H. Ryu, N. Y. Chong, and M. T. Mason, "Fast radiation mapping and multiple source localization using topographic contour map and incremental density

efficient video streaming in UAV-enabled wireless networks: A safe-DQN approach," in *GLOBECOM 2020-2020 IEEE Global Communications Conference*. IEEE, 2020, pp. 1–7.

[195] R. Zhao, J. Xia, Z. Zhao, S. Lai, L. Fan, and D. Li, "Green MEC networks design under UAV attack: A deep reinforcement learning approach," *IEEE Transactions on Green Communications and Networking*, 2021.

[196] C. Wu, S. Shi, S. Gu, L. Zhang, and X. Gu, "Deep reinforcement learning-based content placement and trajectory design in urban cache-enabled UAV networks," *Wireless Communications and Mobile Computing*, vol. 2020, 2020.

[197] Q. Liu, L. Shi, L. Sun, J. Li, M. Ding, and F. Shu, "Path planning for UAV-mounted mobile edge computing with deep reinforcement learning," *IEEE Transactions on Vehicular Technology*, vol. 69, no. 5, pp. 5723–5728, 2020.

[198] J. Shi, L. Zhao, X. Wang, W. Zhao, A. Hawbani, and M. Huang, "A novel deep Q-learning-based air-assisted vehicular caching scheme for safe autonomous driving," *IEEE Transactions on Intelligent Transportation Systems*, 2020.

[199] S. Jeong, J. Bito, and M. M. Tentzeris, "Design of a novel wireless power system using machine learning techniques for drone applications," in *Wireless Power Transfer Conference (WPTC)*. IEEE, 2017, pp. 1–4.

[200] K. Li, W. Ni, E. Tovar, and A. Jamalipour, "Deep Q-learning based resource management in UAV-assisted wireless powered IoT networks," in *IEEE International Conference on Communications (ICC)*. IEEE, 2020, pp. 1–6.

12. A reliable and energy efficient dual prediction data reduction approach for WSNs based on Kalman filter

[1] Wu, Yu, et al. "To Transmit or Predict: An Efficient Industrial Data Transmission Scheme With Deep Learning and Cloud-Edge Collaboration." IEEE Transactions on Industrial Informatics (2023).

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tion platform including a sensor, an edge gateway, and a cloud server is built, and drastically changing real vibration data are collected to validate the proposed scheme. The results show that the proposed scheme can reduce 88.66% of data transmission while guaranteeing deviations less than 0.1.

***Index Terms*—Deep learning (DL), dual prediction scheme (DPS), time series prediction, industrial Internet of Things (IIoT), cloud-edge collaboration, transmission reduction.**

I. INTRODUCTION

IN SMART factory, a large number of applications are deployed on the cloud platform [1]. These applications, such

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Existing data transmission reduction methods are generally based on filtering, sampling, and compression [3]. Most of the current works is an extension and synthesis of these three basic methods under specific problems [2], [4], [5]. However, these works are not suitable for sharply varying data. And they cannot ensure the data obtained by the cloud with adequate accuracy, which directly affects the performance of the applications. The dual prediction scheme (DPS) is an efficient approach to reduce data transmission while ensuring data accuracy. It runs the same prediction model on both the sender and receiver of the data. Furthermore, the data are only transmitted when the predicted deviation is greater than a given threshold [6], [7].

The time series data consist of the specific value of the physical quantity and the timestamp that records when the value was collected. The existing works on DPS only reduce the transmission of the value but not the timestamp [8]. In the process of constructing the testbed and collecting real data, we notice that the timestamp occupies much more space than the value. The neglected timestamp will significantly increase the amount of data transmission. Moreover, the existing works on DPS focus on wireless sensor networks (WSN) [8], [9], [10]. The wireless sensors tend to collect slowly changing data, such as temperature and humidity [11]. Limited by the application scenarios and computing capabilities of wireless sensors, these works can only use simple prediction models in DPS. They cannot be applied to the fast-changing data required by cloud applications. Since deep learning (DL) models can better capture the temporal correlation and nonlinear relationship among the time series data, it is more suitable for predicting the sharply varying industrial data [12], [13]. Meanwhile, edge gateways in smart factory have much

参考文献：

reduction technique for reducing data transmission in IoT sensors," in *Proc. IEEE 15th Int. Wireless Commun. Mobile Comput. Conf.*, 2019, pp. 168–173.

[5] M. Ibrahim, H. Harb, A. Mansour, A. Nasser, and C. Oswald, "All-in-one: Toward hybrid data collection and energy saving mechanism in sensing-based IoT applications," *Peer-to-Peer Netw. Appl.*, vol. 14, no. 3, pp. 1154–1173, 2021.

[6] B. Chreim, J. Nassar, and C. Habib, "Radar-regression based energy-aware data reduction in WSN: Application to smart grids," in *Proc. Int. Conf. Adv. Inf. Netw. Appl.*, Springer, 2021, pp. 1–14.

[7] G. M. Dias, B. Bellalta, and S. Oechsner, "The impact of dual prediction schemes on the reduction of the number of transmissions in sensor networks," *Comput. Commun.*, vol. 112, pp. 58–72, 2017.

[8] A. Fathalla, K. Li, A. Salah, and M. F. Mohamed, "An LSTM-based distributed scheme for data transmission reduction of IoT systems," *Neurocomputing*, vol. 485, pp. 166–180, 2022.

[9] H. Wang, Z. Yemeni, W. M. Ismael, A. Hawbani, and S. H. Alsamhi, "A reliable and energy efficient dual prediction data reduction approach for WSNS based on kalman filter," *IET Commun.*, vol. 15, no. 18, pp. 2285–2299, 2021.

[10] K. Jain and A. Kumar, "A lightweight data transmission reduction method based on a dual prediction technique for sensor networks," *Trans. Emerg. Telecommun. Technol.*, vol. 32, no. 11, 2021, Art. no. e4345.

[11] T. Rault, A. Bouabdallah, and Y. Challal, "Energy efficiency in wireless sensor networks: A top-down survey," *Comput. Netw.*, vol. 67, pp. 104–122, 2014.

[12] I. Kok and S. Ozdemir, "DeepMDP: A novel deep learning based missing data prediction protocol for IoT," *IEEE Internet Things J.*, vol. 8, no. 1, pp. 232–243, Jan. 2021.

collaborative intelligence method of insulator string defect detection for power IIoT," *IEEE Internet Things J.*, vol. 8, no. 9, pp. 7510–7520, May 2021.

[28] M. Gao, R. Shen, L. Shi, W. Qi, J. Li, and Y. Li, "Task partitioning and offloading in DNN-task enabled mobile edge computing networks," *IEEE Trans. Mobile Comput.*, early access, Sep. 21, 2021, doi: 10.1109/TMC.2021.3114193.

[29] X. Chen, J. Zhang, B. Lin, Z. Chen, K. Wolter, and G. Min, "Energy-efficient offloading for DNN-based smart IoT systems in cloud-edge environments," *IEEE Trans. Parallel Distrib. Syst.*, vol. 33, no. 3, pp. 683–697, Mar. 2022.

[30] Z. C. Lipton, D. C. Kale, C. Elkan, and R. Wetzel, "Learning to diagnose with LSTM recurrent neural networks," in *Proc. Int. Conf. Learn. Represent.*, 2016.

[31] Y. Wang, J. Zhou, K. Chen, Y. Wang, and L. Liu, "Water quality prediction method based on LSTM neural network," in *Proc. IEEE 12th Int. Conf. Intell. Syst. Knowl. Eng.*, 2017, pp. 1–5.

[32] X. Li, S. Wu, and L. Wang, "Blood pressure prediction via recurrent models with contextual layer," in *Proc. 26th Int. Conf. World Wide Web*, 2017, pp. 685–693.

[33] S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Comput.*, vol. 9, no. 8, pp. 1735–1780, 1997.

[34] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. Int. Conf. Learn. Represent.*, 2015, pp. 1–15.

[35] H. Sak, A. Senior, and F. Beaufays, "Long short-term memory based recurrent neural network architectures for large vocabulary speech recognition," 2014, *arXiv:1402.1128*.

[36] A. T. Atieh, "The next generation cloud technologies: A review on distributed cloud, fog and edge computing and their opportunities and

13. SDORP: SDN based opportunistic routing for asynchronous wireless sensor networks

[1] Qaisar, Muhammad Umar Farooq, et al. "Reliable and Resilient Communication in Duty Cycled Software Defined Wireless Sensor Networks." 2023 IEEE International Conference on Communications Workshops (ICC Workshops). IEEE, 2023.

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sink node, resulting in data redundancy. To address this issue, the number of forwarding nodes for each node must be controlled using an effective mechanism. This work describes the communication action flow strategy applied to the packet to forward or drop using Eq. (14), where $\mathfrak{F}_x$ is the number of forwarding nodes threshold chosen by the sender node.

$$\overrightarrow{Act}(Sn_x) = \begin{cases} Forward\ \mathfrak{F}_x \leq \lceil 1 + (\ln(r_x)) \rceil;\ REDC_y \leq \frac{\sum_{y=1}^{r_x} REDC_y}{r_x} \\ Drop\ \mathfrak{F}_x > \lceil 1 + (\ln(r_x)) \rceil;\ REDC_y > \frac{\sum_{y=1}^{r_x} REDC_y}{r_x} \end{cases} \quad (14)$$

The SDN controller updates the precedence value based on the residual energy factor. When a node loses 5% of its energy, the SDN controller reevaluates the REDC and updates the nodes' communication strategies in their flow tables.

IV. Performance Evaluation and Discussion

We used a simulator developed in visual studio 2015 (C# WPF) [5] based on the NS3 models to examine the performance of the proposed protocol R^2Com, by taking various simulation parameters into account listed in Table III. The nodes are deployed at random, and the sink is positioned in the region's center. For simulation convenience, the controller is set to the sink position. Each node employs the BoX-MAC [15] and has the same active (1s) and sleep (2s) durations. The nodes are given 0.5J battery powers and are instructed to use energy in accordance with the energy model described in [5]. To ensure simulation accuracy, we ran the simulations 25 times to obtain the average values for the results.

The proposed protocol R^2Com is evaluated using the following parameters. i) **Average Energy Consumption**: It determines the energy consumed by all nodes during the simulation phase. ii) **Packet Delivery Ratio (PDR)**: It emphasizes the

approach on the data plane by considering direct and recommended trust, as well as the residual energy of the nodes with their probability distributions, to efficiently prioritize the nodes in the selection of high trustworthy forwarder nodes in each transmission phase. This approach also ensures network resilience. Second, on the control plane, it employs an effective reliable approach in which the controller computes the reliable reverse path to assign communication strategies to each node. ETERS and ETMRM both did not consider effectively distributing node trustworthiness and other parameters to improve the network's reliability and average energy consumption.

Fig. 4b depicts the packet delivery ratio result, demonstrating how the result gradually decreases as the number of malicious nodes increases. The proposed protocol R^2Com outperforms state-of-the-art protocols in terms of reliability and resilience in the selection of forwarder nodes to transmit data using probability distributions that efficiently managed to prioritize the nodes under the malicious nodes. ETERS and ETMRM results fall short in the proper distribution of trust during relay node selection and also in the efficient path selection technique when compared to our proposed protocol.

Fig. 4c depicts the average latency result, demonstrating how the result gradually increases as the number of malicious nodes increases. The proposed protocol R^2Com outperforms the state-of-the-art protocols in terms of average latency results because it uses the direct and recommended trust distributions of the nodes with the EDC metric to provide latency reliability. The data packet is relayed to the sink via highly reliable nodes with shortest paths. ETERS and ETMRM both use the trustworthy routing technique without focusing on latency by shortening the path in the presence of malicious nodes.

参考文献：

worthy, signal-to-interference noise ratio, and residual energy distributions in the reliable communication flow. Furthermore, the SDN controller manages the computation of these distributions with EDC to reduce the resources of data plane nodes while improving network lifetime. Although the presence of malicious nodes in the network consumes a lot of energy, it still provides a more reliable and resilient approach to network functionality. ETERS and ETMRM employ the reliability approach in the communication process, but they lack an energy-efficient and balanced approach to effectively utilizing the trustworthiness of network nodes under malicious nodes.

V. Conclusion

A reliable and resilient communication is introduced with effective management in duty cycled software defined wireless sensor networks. It focuses on the reliability of assigning communication strategies to each node through the control plane, as well as the reliability and resilience of data communication

[2] R. Kumar, U. Venkanna, and V. Tiwari, "Eomcsr: An energy optimized multi-constrained sustainable routing model for sdwsn," *IEEE Transactions on Network and Service Management*, 2021.

[3] A. Fausto, G. Gaggero, F. Patrone, and M. Marchese, "Reduction of the delays within an intrusion detection system (ids) based on software defined networking (sdn)," *IEEE Access*, vol. 10, pp. 109850–109862, 2022.

[4] S. S. G. Shiny, S. S. Priya, and K. Murugan, "Control message quenching-based communication protocol for energy management in sdwsn," *IEEE Transactions on Network and Service Management*, 2022.

[5] M. U. F. Qaisar, X. Wang, A. Hawbani, L. Zhao, A. Y. Al-Dubai, and O. Busaileh, "Sdorp: Sdn based opportunistic routing for asynchronous wireless sensor networks," *IEEE Transactions on Mobile Computing*, 2022.

[6] M. U. F. Qaisar, X. Wang, A. Hawbani, A. Khan, A. Ahmed, and F. T. Wedaj, "Torp: load balanced reliable opportunistic routing for asynchronous wireless sensor networks," in *2020 IEEE 19th International Conference on Trust, Security and Privacy in Computing and Communications (TrustCom)*, pp. 1384–1389, IEEE, 2020.

[7] E. Ghadimi, O. Landsiedel, P. Soldati, S. Duquennoy, and M. Johansson, "Opportunistic routing in low duty-cycle wireless sensor networks," *ACM Transactions on Sensor Networks (TOSN)*, vol. 10, no. 4, pp. 1–39, 2014.

[8] R. Feng, X. Han, Q. Liu, and N. Yu, "A credible bayesian-based