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A methodology for optimizing Time-Sensitive Networking scheduling schemes based on a dual graph attention network

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Time-Sensitive Networking (TSN) is pivotal for enabling deterministic communication in industrial automation and cyber-physical systems, where network component failures can cause severe service disruptions. However, due to the complex and dynamic nature of flows, designing optimal scheduling schemes that simultaneously satisfy constraints on end-to-end latency and reliability remains a challenge. To address this, this paper proposes a novel methodology for optimizing TSN scheduling based on a Dual Graph Attention Network (Dual-GAT). The Dual-GAT is incorporated to enhance feature extraction for scheduling and improve scheduling accuracy. The optimization of scheduling schemes is implemented in the TSN scheduling framework abstracted as a Markov decision process (MDP). Unlike traditional DRL approaches that struggle with spatial graph dependencies, our Dual-GAT acts as a feature encoder and cooperates with the MDP framework to jointly process flow requirements and hardware port constraints through parallel attention blocks. This architecture enables the agent to perceive intricate spatial relationships and structural topology metrics. This data-driven framework learns to generate scheduling strategies that inherently minimize latency and maximize reliability. As a case study, TSN scheduling of the in-vehicle centralized electrical/electronic architecture is used to demonstrate the applicability of the methodology. The proposed model is beneficial to optimize the design of the in-vehicle electrical/electronic architecture.

Keywords: In-vehicle network failure, Time-Sensitive Networking, Graph Attention Network, Deep reinforcement learning, Scheduling strategy optimization, rerouting mechanism.

1. Introduction

The automotive industry is undergoing a shift toward centralized electrical/electronic architectures to support autonomous driving and advanced driver-assistance systems [1]. Time-Sensitive Networking (TSN), a set of IEEE 802.1 sub-standards, has emerged as the foundational technology for these next-generation in-vehicle networks by providing deterministic low-latency communication [2]. However, encompassing hundreds of flows and multi-hop topologies results in network complexity increasing. Traditional static scheduling methods configuration (e.g., satisfiability modulo theories [3] and integer linear programming [4, 5]) become computationally intractable and lack the flexibility to handle sudden network failures.

Reliability in TSN is often compromised by physical link interruptions, which can lead to catastrophic system failures in safety-critical applications [6]. Existing heuristic algorithms often rely on fixed routing paths that cannot adapt to dynamic topology changes. Peng et al. [7] studied a heuristic resilient and performant scheduling strategy to achieve fault-tolerant and time-sensitive scheduling. Min et al [6] investigated efficient routing and scheduling strategies for fault-tolerant TSN to support FRER with reduced complexity. While deep reinforcement learning (DRL) offers a potential solution for adaptive scheduling, DRL agents struggle to perceive the spatial dependencies of a network graph [8, 9]. Therefore, some studies are introduced graph attention network (GAT) with DRL to achieve better scheduling strategies [10, 11].

This paper addresses these challenges by proposing a scheduling methodology that combines Dual Graph Attention Networks (Dual-GAT) with a robust DRL framework. Our approach specifically integrates structural topology metrics to empower the agent with global network awareness, enabling millisecond-level rerouting and rescheduling upon link failure. Finally, we make an analysis based on the model results of the in-vehicle TSN.

The remainder of this paper is structured as follows. Section 2 describes the methodology of the integration of Dual-GAT and DRL for the in-vehicle TSN scheduling. Section 3 presents a case study and results. Finally, Section 4 concludes the paper.

2. Methodology

We proposed an integrated methodology for optimizing TSN scheduling schemes by combining a Dual-GAT and DRL. The methodology can be divided into four steps.

In this methodology of Fig. 1, step 1 aims to define the system state by extracting multiple-dimensional feature vectors that represent both flow priorities and structural network topology metrics. Step 2 intends to construct a Dual-GAT model, utilizing parallel flow and port message attention blocks to capture the intricate spatial interdependencies between scheduling operations and port resources. Step 3 is used to establish the DRL scheduling framework, modelled as a Markov Decision Process (MDP), to optimize scheduling configurations. Based on step 3, a dynamic rerouting mechanism and fault-tolerance analysis can be developed to evaluate the adaptive performance of the scheduling schemes under link failure scenarios in step 4.

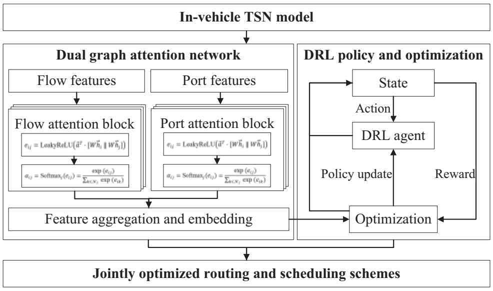

Fig. 1. The framework of the integrated methodology.

2.1. *State space and feature engineering*

The scheduling task is modeled as an MDP defined by the tuple (S, A, P, R, γ). The framework utilizes a dual attention network to capture features from both the flow requirements and the hardware constraints of the ports. The state S_t consists of two sets of 12-dimensional raw feature vectors. Flow features include 10 basic scheduling metrics (e.g., waiting time, remaining work) and 2 innovative metrics (link centrality and flow priority). Port features include 8 basic metrics (e.g., port free time, working flag) and degree centrality, betweenness centrality, closeness centrality, and real-time port load. These feature calculations can effectively identify critical links and allocate resources reasonably.

Link Centrality helps the model avoid over-congesting links that are essential for many other flows. For a flow f , this is defined as the average betweenness of the links along its predefined path P_f in Eq. (1):

$$C_{\text{link}}\left(f\right)=\frac{1}{\left|P_f\right|}\sum_{e\in P_f}g\left(e\right) \tag{1}$$

where $g\left(e\right)$ is the edge betweenness centrality.

Degree Centrality measures the direct connectivity of a port v in Eq. (2).

$$C_{\text{D}}\left(v\right)=\frac{\deg\left(v\right)}{n-1} \tag{2}$$

where $\deg\left(v\right)$ is the number of links connected to the switch and n is the total number of nodes.

Betweenness Centrality quantifies the role of a port v as a bridge in Eq. (3).

$$C_{\text{B}}\left(v\right)=\sum_{s\neq v\neq t}\frac{\sigma_{st}\left(v\right)}{\sigma_{st}} \tag{3}$$

where σ_{st} is the total number of shortest paths between node s and t , and $\sigma_{st}\left(v\right)$ is the number of those paths that pass through v .

Closeness Centrality measures how central a port is relative to all others in Eq. (4).

$$C_{\text{C}}\left(v\right)=\frac{n-1}{\sum_{u\neq v}d\left(v,u\right)} \tag{4}$$

where $d\left(v,u\right)$ is the shortest path distance between nodes v and u .

Real-time port load represented by the port's occupancy status at time t in Eq. (5).

$$L_t\left(v\right)=\frac{T_{\text{occupied}}\left(v,t\right)}{T_{\text{total}}} \tag{5}$$

This dynamic feature provides the agent with immediate feedback on port congestion, preventing the assignment of packets to ports that are already saturated.

2.2. *Dual-GAT architecture*

The methodology employs a stack of dual attention layers. Each layer contains a flow message attention block and a port message attention block.

For a node i with a feature vector $\vec{h}_i$, the relationship with its neighbor $j\in\mathcal{N}_i$ is transformed by a weight matrix $W\in\mathbb{R}^{d'\times d}$. The attention score e_{ij} is computed in Eq. (6):

$$e_{ij}=\text{LeakyReLU}\left(\vec{a}^T\cdot\left[W\vec{h}_i\|W\vec{h}_j\right]\right) \tag{6}$$

where $\vec{a}$ is the learnable attention vector. $[\cdot\|\cdot]$ symbolizes the concatenation of two vectors, and LeakyReLU $(\cdot)$ represents the activation function.

To make coefficients comparable across different nodes, we apply the softmax function in Eq. (7):

$$\alpha_{ij}=\text{Softmax}_j\left(e_{ij}\right)=\frac{\exp\left(e_{ij}\right)}{\sum_{k\in\mathcal{N}_i}\exp\left(e_{ik}\right)} \tag{7}$$

The output feature $h_i^{'}$ is a weighted combination of its neighbors in Eq. (8):

$$h_i^{'}=\sigma\left(\sum_{j\in\mathcal{N}_i}\alpha_{ij}W\vec{h}_i\right) \tag{8}$$

where σ is an activation function like ELU.

2.3. *DRL training with Q-Learning logic*

The policy update follows a deep Q-network logic using a target network for stability.

The agent minimizes the Mean Squared Error (MSE) of the Q-value prediction in Eq. (9):

$$Loss=\mathbb{E}\left[\left(Q\left(s,a;\theta\right)-\left(r+\gamma\max_{a'}Q\left(s',a';\theta^-\right)\right)\right)^2\right] \tag{9}$$

where θ^- represents the target network parameters updated via soft-update: $\theta^-=\tau\theta^-+\left(1-\tau\right)\theta$.

The reward R_t incentivizes the minimization of the end-to-end delay in Eq. (10):

$$R_t = C_{\mathrm{LB}}\left(S_t\right) - C_{\mathrm{LB}}\left(S_{t+1}\right) \tag{10}$$

This step-wise difference ensures the agent receives feedback for every flow assignment that contributes to reducing overall network latency.

3. Case study

The in-vehicle network (IVN) significantly impacts the performance of the high-level autonomous vehicles. As a crucial communication solution for future intelligent connected vehicles, TSN has low latency, high security, and deterministic communication capabilities [10, 12, 13]. The IVN consists of two essential components: the network topology and the information flow. In this paper, we take a typical topology of the centralized E/E architecture in Fig. 2 as an example to illustrate the applicability of the proposed methodology. L stands for LiDAR, R is radar, C refers to camera, and T represents the telematics module. SW denotes switch. SW and its connected zone controller (ZC) comprise the zone controller unit (ZCU). SW and its connected high-performance controller (HC) comprise the high-performance computing (HPC).

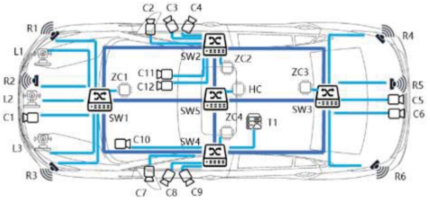

Fig. 2. The in-vehicle topology [10].

Creating a system model that accurately represents the IVN environment is crucial for optimizing the in-vehicle TSN architecture. This network is formed by the interconnections between sensors, controllers, and actuators. Extracted as a directed graph G, the IVN model can mathematically describe the E/E architecture of TSN as [4] in Eq. (11):

$$\begin{cases} G \equiv (N,\ E) \\ N = \{n_1,\ n_2, \ldots, n_N\} \\ E \subseteq \{e_{ij} \mid i, j \in N, i \neq j\} \end{cases} \tag{11}$$

where N denotes the set of nodes. E represents the subset of possible ordered pairs for distinct nodes. e_{ij} refers to the link from node n_i to node n_j.

For the IVN, the flow attribute digitally characterizes information exchange between nodes within the network topology. The properties of a specific flow can be mathematically expressed by Eq. (12):

$$f_k \equiv (n_{s,k}, n_{d,k}, c_k, T_k, d_k, \tau_k) \tag{12}$$

where $n_{s,k}$, $n_{d,k}$ $\in$ N signifies the source node and destination node of the flow f_k. c_k refers to the required bandwidth of the flow f_k. T_k and d_k correspond to the period and deadline of the flow f_k. τ_k denotes the priority of the flow f_k.

In advanced autonomous vehicles, the multitude of signals generated by diverse sensors and controllers are abstracted as Time-Triggered (TT) flows to facilitate centralized network scheduling. The parameters of the TT flows in the IVN are shown in Table 1 [10].

Table 1. Parameters of in-vehicle communication flows.

Flow	Period (ms)	Deadline (ms)	Payload (Mb/s)
LiDAR	2	2	60
Radar	2	2	5
Camera	2	2	20
Telematics	4	4	20
Control-1ms	1	1	10
Control-4ms	4	4	10

The study utilizes a simulated in-vehicle TSN environment with 26 ports and a 143-flow dataset, including about 400 flows. The topology includes 5 core switches (SW 1-5) and 4 ZCUs, as defined by a 10x10 port matrix. The parameters for Dual-GAT and DRL are presented in Table 2.

Table 2. Parameters for Dual-GAT and DRL.

Parameters	Value
The number of GAT layers	2
Attention heads	4
Update epochs	4
Discount factor	1
Learning rate	0.0007

Through hyperparameter tuning, the learning rate plays a critical role in balancing convergence stability and scheduling optimality. As shown in Fig. 3, the model with a learning rate of 0.0007 achieves higher rewards more quickly compared to other learning rates. The reward for a learning rate of 0.0006 is higher than that of 0.0008 in the early stage, although the convergent reward is almost the same.

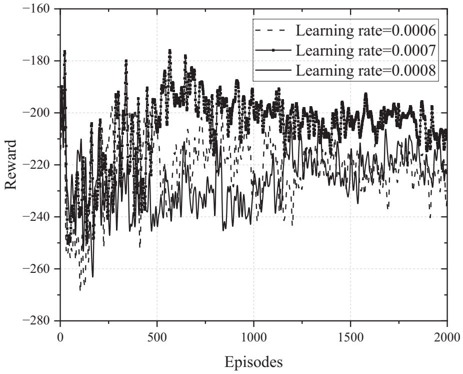

Fig. 3. Comparison of the learning rate on performance.

For the rerouting mechanism upon failure, the dynamic pair mask in the environment is updated. Setting the probability of choosing the failed ports in the softmax layer forces the DAN to find an alternative route based on port centrality and current load. In Fig. 4, the failure of the links in the IVN leads to a lower reward. The higher the probability of failure, the lower the convergence value of the reward curve. Despite the stochastic injection of faults, the moving average reward remained stable, indicating the GAT successfully extracted invariant topological features that allow the model to generalize across different failure scenarios.

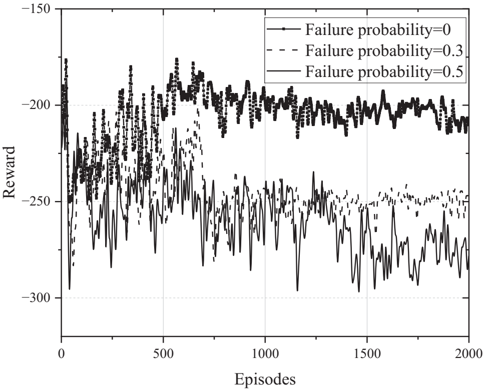

Fig. 4. Comparison of the failure probability on performance.

4. Conclusion

This methodology provides a robust framework for TSN scheduling by integrating a Dual-GAT and DRL. By embedding structural topology metrics directly into the state space, the agent achieves an advanced spatial awareness of the network graph that is different from traditional static methods. This methodology facilitates rerouting and rescheduling through the update of dynamic pair masks during sudden physical link failures. Ultimately, the integration of graph-based feature extraction and data-driven optimization provides a scalable, self-healing solution for in-vehicle centralized E/E architectures, effectively balancing end-to-end latency with network reliability.

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References

1. Zou Y., Sun W., Zhang X., Liu J., Wen Y., Ma W., Research on the Development of Multi Domain Electronic and Electrical Architecture Technology for Intelligent Connected Vehicles. Automotive Engineering, 2023. 46(6): 895-909.
2. Luo F., Wang Z., Zhang B., Impact analysis and detection of time-delay attacks in time-

sensitive networking. Computer Networks, 2023. 234: 109936.

3. Feng Z., Deng Q., Cai M., Li J., Efficient Reservation-based Fault-Tolerant Scheduling for IEEE 802.1Qbv Time-Sensitive Networking. Journal of Systems Architecture, 2022. 123: 102381.
4. Atallah A., Hamad G., Mohamed O., Routing and Scheduling of Time-Triggered Traffic in Time-Sensitive Networks. IEEE Transactions on Industrial Informatics, 2020. 16(7): 4525-4534.
5. Cui X., Li B., Wang S., Zhang S., Yang X., Ren Y., Xiao Y., Timeliness-oriented rush repair optimization of workforce scheduling and routing for logically complex systems under uncertainty. Reliability Engineering & System Safety, 2025. 253: 110574.
6. Min J., Kim W., Paek J., Govindan R., Effective Routing and Scheduling Strategies for Fault-Tolerant Time-Sensitive Networking. IEEE Internet of Things Journal, 2024. 11(6): 11008-11020.
7. Peng G., Wang S., Huang T., Li F., Zhao K., Huang Y., Xiong Z., FastTS: Enabling Fault-Tolerant and Time-Sensitive Scheduling in Space-Terrestrial Integrated Networks. IEEE Journal on Selected Areas in Communications, 2024. 42(12): 3551-3565.
8. Yang L.,Wei Y.,Yu F., Han Z., Joint Routing and Scheduling Optimization in Time-Sensitive Networks Using Graph-Convolutional-Network-Based Deep Reinforcement Learning. IEEE Internet of Things Journal, 2022. 9(23): 23981-23994.
9. Tian Z., Zhou X., Liao Z., Sun M., He F., GTSNet: A Generalized Traffic Scheduler for Time-Sensitive Networking Based on Graph Neural Network. IEEE Transactions on Industrial Informatics, 2025. 21(1): 208-217.
10. Sun W., Zou Y., Guan N., Zhang X., Du G., Wen Y., Graph Attention Network–Based Deep Reinforcement Learning Scheduling Framework for in-Vehicle Time-Sensitive Networking. IEEE Transactions on Industrial Informatics, 2024. 20(7): 9825-9836.
11. Wang R., Wang G., Sun J., Deng F., Chen J., Flexible Job Shop Scheduling via Dual Attention Network-Based Reinforcement Learning. IEEE Transactions on Neural Networks and Learning Systems, 2024. 35(3): 3091-3102.
12. Zhang C., Wen X., Li C., Zheng W., Yu L., Lu Z., Dynamic Rapid Scheduling Algorithm for Vehicle Time Sensitive Communication based on CILP and AGA. IEEE Transactions on Vehicular Technology, 2023. 72(11): 1-14.
13. Lv J., Zhao Y., Wu X., Li Y., Wang Q., Formal Analysis of TSN Scheduler for Real-Time Communications. IEEE Transactions on Reliability, 2021. 70(3): 1286-1294.