

JOINT ROUTING AND SCHEDULING OPTIMIZATION OF TRAIN COMMUNICATION NETWORKS BASED ON IMPROVED GENETIC ALGORITHM

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Received April 2025; revised August 2025

ABSTRACT. *Time sensitive networking (TSN) can provide highly reliable and low-latency deterministic communication for train communication network (TCN), which can effectively enhance control performance in scenarios such as flexible train formation and automatic train operation. To effectively enhance the performance of TCN, a joint routing and scheduling optimization for time-triggered (TT) flow in TCN was proposed. The TCN topology and flow model are established, the scheduling priority of all TT flows is obtained according to frame periods and frame sizes, and a candidate path set is selected based on K shortest path and flow conflict degree. In addition, the network scheduling problem is abstracted as a job-shop scheduling problem, and the makespan and worst end-to-end delay of all TT flows are selected as the optimization objectives. A scheduling optimization method based on adaptive population migration genetic algorithm (APM-GA) is designed and two populations are initialized based on random strategy and scheduling priority sequence strategy. After each round of independent evolution, the inferior solutions of each population are migrated to the superior solutions of the other. The crossover and mutation probabilities are dynamically adjusted based on the training process. Simulation experiments were conducted in the actual TCN scenarios, the experimental results show that compared with traditional methods, the proposed method can effectively improve the scheduling performance and provide guidance for the engineering application of TSN.*

Keywords: Train communication network, Time-sensitive networking, Routing selection, Traffic scheduling, Improved genetic algorithm

1. Introduction. As a core sub-system of high-speed trains, train communication network (TCN) is primarily responsible for the timely and reliable transmission of control instructions and condition information from critical subsystems, such as traction, braking, doors, and air-conditioning, as well as passenger service. The communication delay and jitter of industrial Ethernet will affect the control performance of networked control system [1,2], so the improvement of TCN communication performance is of great significance to ensure the safety and intelligent level of train operation [3], especially the control performance in scenarios such as flexible train formation and automatic train operation.

Due to its high transmission rate and wide compatibility, Ethernet-based TCN has gradually replaced traditional wired bus technologies, such as wire train bus (WTB) and multifunction vehicle bus (MVB). However, current real-time data protocols for Ethernet still rely on conventional carrier-sense and collision detection mechanisms, which lead to unpredictable queuing delays and packet collisions. These limitations prevent effective guarantees for deterministic transmission of time-sensitive traffic. Moreover, with the continuous advancement of train intelligence, higher requirements for the real-time performance and reliability of TCN are emerging.

Time sensitive networking (TSN) is standardized by the IEEE 802.1 TSN Task Group, which includes time-triggered (TT) flows, audio video bridging (AVB) flows, and best effort (BE) flows. Built upon standard Ethernet, TSN extends its capabilities with features such as time synchronization, time aware shaper (TAS) mechanism, and bandwidth reservation. Time synchronization serves as the foundation for all TSN mechanisms. It is implemented based on the IEEE 802.1AS protocol, which defines a generalized precision time protocol (gPTP) for nanosecond-level clock synchronization across network nodes. In TAS mechanism, a gate is set up in the queue of each port, the traffic is transmitted only when the gate is open, and the opening and closing time of each gate is controlled by the gate control list (GCL), which is generated based on traffic scheduling. According to the international train standard IEC 61375-3-4, monitoring data and process data are very similar to TT flows, TSN can effectively ensure the deterministic and real-time transmission of time-sensitive traffic [4], so it is regarded as the most promising solution for next-generation train communication networks. Currently, European projects, such as Shift2Rail and Safe4RAIL, have adopted TSN for future train communication architectures, and TSN technologies have also been partially applied in new-generation TCN in China. TSN has ability of deterministic low-latency transmission for time-sensitive traffic such as monitoring data and process data, and supporting the transmission of non-real-time traffic such as passenger information and configuration data [5,6].

To achieve deterministic and low-latency communication, the TAS mechanism is introduced in TSN by IEEE 802.1Qbv, and a GCL can achieve mutual isolation and precise timing of traffic transmission [7]. Therefore, generating an appropriate GCL becomes the key challenge of TSN traffic scheduling, which can be considered as a well-known NP-Hard problem. Many researchers have carried out extensive work on scheduling periodic traffic in automotive and train communication networks [8,9]. Heuristic algorithms, including genetic algorithm (GA) [10], tabu search (TS) [11], and ant colony optimization (ACO) [12], have been used for traffic scheduling in TSN. In addition, although the shortest path first (SPF) algorithm is recommended by IEEE 802.1Qca for routing, it may lead to congestion on certain links under heavy traffic loads, thereby failing to utilize network bandwidth effectively. To address these issues, some researchers have proposed various routing algorithms that consider traffic periods, maximum load, and schedulability. Huang et al. proposed a time scheduling-aware routing algorithm, the flow period and analyzed the importance of routing planning for TSN traffic scheduling [13]. Nayak et al. explored the influence of different TT flow routing algorithms on its schedulability, the maximum flow scheduling load is taken as the routing measurement criterion, and integer linear programming (ILP) is used to solve the traffic scheduling problem, which can effectively improve the efficiency of scheduling instructions [14].

While routing and scheduling are treated independently in IEEE 802.1Qbv, some studies have shown that successful scheduling of time-triggered (TT) flows requires not only proper configuration of gate schedules but also the selection of suitable routing paths. Joint consideration of routing and scheduling is crucial for improving schedulability and achieving better optimization results [15]. Consequently, joint routing and scheduling

(JRS) in TSN has become a prominent research focus in both academia and industry. Xu et al. proposed a joint routing and scheduling method based on satisfiable modulo theory (SMT) and optimization modulus theory, which not only ensures the schedulability of the network but also improves the utilization rate of the network [16]. Schweissguth et al. constructed a mathematical model for TSN network traffic routing and joint time slot scheduling, and a feasible solution was obtained by ILP [17]. Vlk et al. proposed a joint routing scheduling method based on constrained programming and logical benders decomposition, and analyzed the influence of routing algorithms such as SPF and load balancing (LB) on traffic schedulability and computing time [18]. However, ILP and SMT are used to achieve high accuracy scheduling results, but these are not suitable for larger networks due to their computational complexity. On the contrary, heuristic algorithms have been introduced to provide near-optimal solutions within reasonable time, but most existing studies lack validation in realistic train scenarios, and these optimization algorithms need to be enhanced for TCN applications. Moreover, it should be particularly noted that GA is a stochastic search technique which is widely solved in various optimization problems [19], but the initialization of the population, crossover probability and mutation probability may significantly influence the performance of GA [20].

Based on the aforementioned analysis, a joint routing and scheduling method based on APM-GA is proposed for TCN. TT flows are prioritized for scheduling according to frame period and frame size, and candidate paths are selected by the K-shortest path algorithm and inter-flow conflict degree to avoid slot collisions. In addition, the TCN scheduling problem is abstracted as a no-wait scheduling problem, and a novel adaptive population migration genetic algorithm (APM-GA) is developed to optimize makespan and worst end-to-end delay, which can obtain deterministic scheduling results with low latency and meet the requirements of TSN-based TCN.

The remainder of the paper is organized as follows. Section 2 models the TCN scheduling problem, which includes TCN topology and flow modeling, no-wait scheduling problem abstraction of TSN scheduling. Section 3 presents the routing selection method and APM-GA algorithm in detail, along with a thorough elaboration of the joint routing and scheduling optimization implementation process. Section 4 analyzes the experimental results and validates the effectiveness of the proposed method. The conclusion is provided in Section 5.

2. Modeling of TCN Scheduling.

2.1. Topology model. According to the international train standard IEC 61375-3-4, the train communication network includes the Ethernet train backbone (ETB) and the Ethernet consist network (ECN). Data communication between different vehicles is realized through ETB, while the data communication between onboard devices is realized through ECN.

Based on IEC 61375, the topology of the next-generation train communication network is designed by the EU Shift2Rail project, a TSN-based TCN architecture is shown in Figure 1. The ETB consists of two redundant lines (Line A and Line B), and TSN switches are deployed at the ECN layer, forming a ring-shaped sub-net composed of 8 TSN switches. All switches and terminal devices maintain precise time synchronization, time-aware shaper (TAS) is configured at each output port of the switch to enable low-latency and deterministic transmission of TT (time-triggered) flows. In addition, the TCN topology provides redundancy in links, network devices, and key terminal devices, which can enhance the overall reliability of TCN.

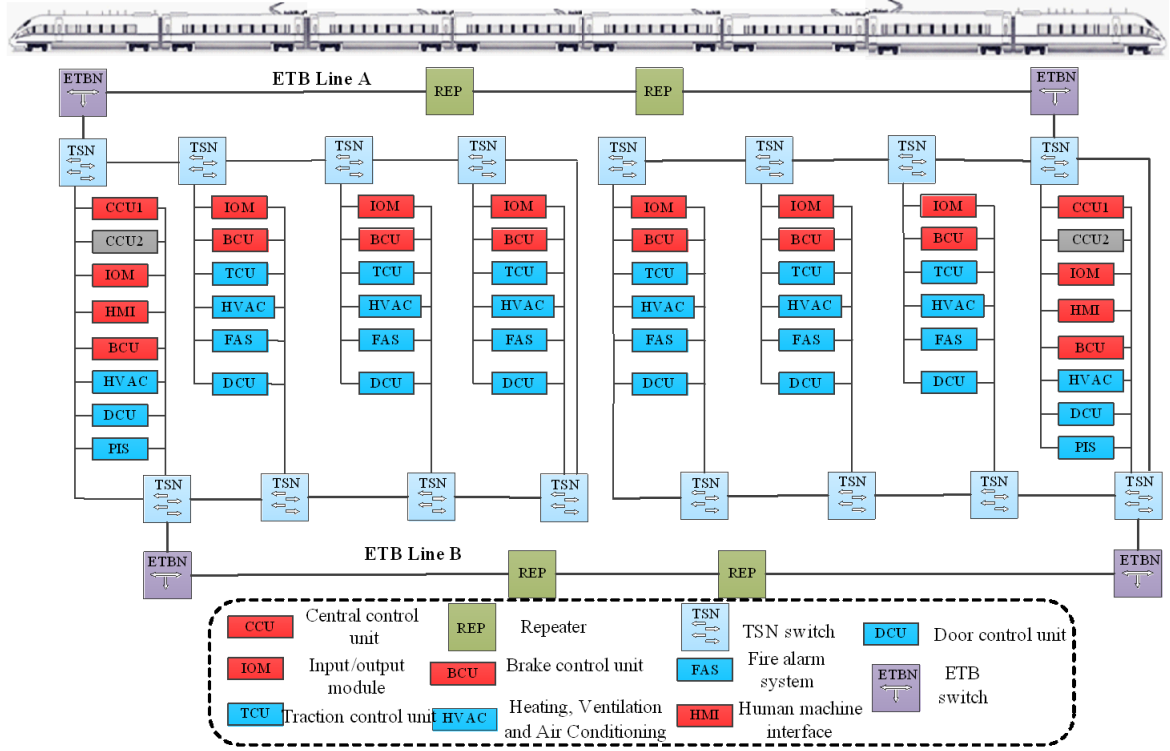


FIGURE 1. Train communication network architecture based on TSN

The TCN topology can be regarded as a directed graph, which can be defined as follows:

$$\begin{cases} G \equiv (V, L) \\ V = ES \cup CS \end{cases} \quad (1)$$

where V represents the set of all communication nodes, L denotes the set of physical links, $ES = \{es_0, es_1, \dots, es_n\}$ represents all terminal devices, and $CS = \{cs_0, cs_1, \dots, cs_m\}$ represents all switches. $A \in R^{N \times M}$ is defined as an adjacency matrix, $A_{ij} = 1$ means the nodes i and j are connected, and $A_{ij} = 0$ means the nodes i and j are not connected.

2.2. Flow model. TCN data type includes monitoring data, process data, message data, streaming data, and best-effort delivery data in IEC 61375, which is listed in Table 1. Monitoring data and process data are periodic data and directly related to the safety of train operation, which have high real-time and deterministic requirements, so we focus on these data types and consider these data types as TT flows in TSN. In contrast, message data, streaming data, and best-effort data (such as passenger information and system updates) are non-periodic and do not require high real-time performance. Therefore, the monitoring data and process data of TCN are considered as scheduling objects in this paper.

The set of all TT flow F in TCN is periodically transmitted from one network node to another, and the k th TT flow can be expressed as

$$f_k \equiv (v_{src}, v_{dest}, c, s, T, ddl, \phi) \quad (2)$$

where each TT f_k flow contains N data frames, $v_{src} \in V$ is the source node, $v_{dest} \in V$ is the destination node, c and s are the bandwidth and frame size, respectively. T is the period of the information flow, ddl and ϕ represent the end data and the offset time relative to the initial sending time in the period, respectively. The TT flow is periodic, and the minimum common multiple of each TT flow corresponding to the frame period

TABLE 1. Details of TCN data type

Data type	Min period	Max delay	Max jitter	Priority	Data content
Monitoring data	10ms	10ms	10ms	high	TCN initial operation, topology monitoring and detection, etc.
Process data	20ms	10ms	10ms	high	It is closely related to train safety operation, including control instructions of train subsystem and on-board equipment
Message data	non-periodic	100ms	No requirement	low	Train operation condition monitoring, diagnosis, etc.
Streaming data	non-periodic	125ms	No requirement	low	Passenger service data, streaming media data, etc.
Best-effort data	non-periodic	No requirement	No requirement	low	Network software update, system maintenance data download, etc.

is called the superperiod, which can be expressed as

$$T_{hyper} = lcm\{f_1.T, f_2.T, \dots, f_k.T\} \quad (3)$$

where $lcm(\cdot)$ is the least common multiple function.

The end-to-end delay of TT information flow f_k mainly consists of four parts: propagation delay $d_{k,prop}$, transmission delay $d_{k,tran}$, processing delay $d_{k,proc}$ and queuing delay $d_{k,queu}$. Among them, propagation delay $d_{k,prop}$ depends on the transmission medium of the network physical link; processing delay $d_{k,proc}$ mainly depends on the performance of the network switch; transmission delay $d_{k,tran}$ is determined by the data frame size s and network bandwidth c . Queuing delay $d_{k,queu}$ is generated when multiple information flows of the same type need to be sent through the same port at the same time, which is affected by the load of each link in the current network, the real-time requirement of TT flows cannot be met.

2.3. Scheduling model for TSN. The basic traffic scheduling mechanism is defined in the IEEE 802.1Qbv standard, but it is not clear how to configure scheduling to achieve a bounded end-to-end network delay. In addition, guard bands are created in the TSN mechanism to bring isolation of TT traffic and best-effort traffic, which can lead to low network bandwidth utilization in TCN. Job shop scheduling problem (JSP) is a well known scheduling problem that tries to schedule each operation on the corresponding machine such that no more than one operation is processed at the same time on any machine. The no-wait job shop scheduling problem (NW-JSP) requires that a job must run to completion without time gaps between the processing of the operations of the job after this job is started. The schedule is expressed by the starting time of each operation of each job. The TSN switches can be mapped to machines performing forwarding operations on packets. A TT flow then corresponds to a sequence of forwarding operations, one for each switch along the given path of the flow, and TT packets must be forwarded without delay which corresponds to the property of NW-JSP. Therefore, the TCN scheduling problem is abstracted as a no-wait job shop scheduling problem [21,22], which can eliminate uncertain network queuing delay, so the queuing delay $d_{k,queu} = 0$. In practice, propagation delay and processing delay can usually be regarded as constants, so the end-to-end delay $D_{k,e2e}$

of TT flow f_k in this paper can be expressed as

$$D_{k,e2e} = \sum_{k=1}^{hop_k} (d_{k,trans} + d_{k,prop}) + \sum_{k=1}^{hop_k-1} d_{k,proc} \quad (4)$$

where hop_k indicates the number of hops that f_k transmits on the path from the source node to the destination node. To ensure high-quality TT traffic transmission with conflict-free, the basic constraints, conflict-free constraints and no-wait constraints are implemented on the traffic model, and the basic constraints includes data frame constraint, end-to-end delay constraint, and network link constraint.

The offset of any TT flow frame must be non-negative, and the scheduling time window of each frame does not exceed the transmission cycle of the TT flow. The frame constraints are defined as follows:

$$\begin{aligned} \forall f_i \in F, \forall j = \left\{ 1, 2, \dots, \frac{f_i \cdot S}{MTU} \right\}, v_a, v_b \in V \\ \left(f_{i,j}^{[v_a, v_b]} \cdot \phi \geq 0 \right) \wedge \\ \left(f_{i,j}^{[v_a, v_b]} \cdot \phi \leq \left(f_{i,j}^{[v_a, v_b]} \cdot T - f_{i,j}^{[v_a, v_b]} \cdot L \right) \right) \end{aligned} \quad (5)$$

where $f_{i,j}^{[v_a, v_b]} \cdot \phi$ and $f_{i,j}^{[v_a, v_b]} \cdot L$ are the offset time and transmission time of the j frame of the i TT flow sent by v_a node to the $[v_a, v_b]$ link, respectively, and the maximum transmission unit (MTU) is the size of a data frame.

To achieve high-quality transmission of TSN network traffic, the delay between the receiving time and the sending time must be less than or equal to the specified maximum end-to-end delay:

$$\begin{aligned} \forall f_i \in F, \forall j = \left\{ 1, 2, \dots, \frac{f_i \cdot S}{MTU} \right\}, v_a, v_b \in V: \\ f_{i,j}^{[v_{n-1}, v_n]} \cdot \phi + f_{i,j}^{[v_{n-1}, v_n]} \cdot L - f_{i,j}^{[v_1, v_2]} \cdot \phi \leq f_i \cdot ddl - \theta \end{aligned} \quad (6)$$

After the routing and forwarding path is determined, any two TT flows cannot overlap in the same time slot on the same transmission link, that is, different flows cannot conflict on the same link:

$$\begin{aligned} \forall f_i, f_j \in F, i \neq j, v_a, v_b \in V: \\ a \in \left[0, \frac{lcm(f_i \cdot T, f_j \cdot T)}{f_i \cdot T} - 1 \right], \beta \in \left[0, \frac{lcm(f_i \cdot T, f_j \cdot T)}{f_j \cdot T} - 1 \right] \\ \left(f_{i,l}^{[v_a, v_b]} \cdot \phi + a \cdot f_i \cdot T + \theta \geq f_{j,k}^{[v_a, v_b]} \cdot \phi + \beta \cdot f_j \cdot T + f_{j,k}^{[v_a, v_b]} \cdot L \right) \vee \\ \left(f_{j,k}^{[v_a, v_b]} \cdot \phi + \beta \cdot f_j \cdot T + \theta \geq f_{i,l}^{[v_a, v_b]} \cdot \phi + a \cdot f_i \cdot T + f_{i,l}^{[v_a, v_b]} \cdot L \right) \end{aligned} \quad (7)$$

When multiple TT flows of the same type from different sources arrive in the same queue at the same time, packet loss will occur due to congestion conflicts, and the certainty of end-to-end delay cannot be guaranteed. Therefore, frame isolation constraints are required to ensure that no overlapping conflicts occur between frames of any two TT flows transmitted in the same queue:

$$\begin{aligned} \forall f_i, f_j \in F, i \neq j, v_a, v_b \in V: \\ a \in \left[0, \frac{lcm(f_i \cdot T, f_j \cdot T)}{f_i \cdot T} - 1 \right], \beta \in \left[0, \frac{lcm(f_i \cdot T, f_j \cdot T)}{f_j \cdot T} - 1 \right] \\ \left(f_{i,l}^{[v_x, v_a]} \cdot \phi + a \cdot f_i \cdot T + f_{i,j}^{[v_x, v_a]} \cdot L + \theta \geq f_{j,k}^{[v_a, v_b]} \cdot \phi + \beta \cdot f_j \cdot T \right) \vee \end{aligned} \quad (8)$$

$$\left(f_{j,k}^{[v_y, v_a]} \cdot \phi + \beta \cdot f_i \cdot T + f_{i,j}^{[v_y, v_a]} \cdot L + \theta \geq f_{i,l}^{[v_a, v_b]} \cdot \phi + a \cdot f_i \cdot T \right) \vee \\ \left(f_i^{[v_a, v_b]} \cdot queue \neq f_j^{[v_a, v_b]} \cdot queue \right)$$

where $f_i^{[v_a, v_b]} \cdot queue$ represents the queue selected by TT flow i after node v_a , and $[v_x, v_a]$ and $[v_y, v_a]$ are any two links of the previous hop of link $[v_a, v_b]$.

The data packet is transmitted to the next switch immediately after the content of one switch is transmitted by using the no-wait traffic constraint, which can eliminate the queuing delay:

$$\forall f_i \in F, \forall i \neq 0, \forall v_a, v_b, v_c \in V: \\ f_{i,j}^{[v_b, v_c]} \cdot \phi = f_{i,j}^{[v_a, v_b]} \cdot \phi + f_{i,j}^{[v_a, v_b]} \cdot L \quad (9)$$

where $[v_b, v_c]$ is the next hop link of $[v_a, v_b]$.

To ensure the high-quality transmission of TT flows with bounded low delay and low jitter, the makespan and worst end-to-end delay of all TT flows are selected as the optimization objectives in this paper. Makespan l_{mspan} indicates the time span from the start time of the super period to the time when all traffic is transmitted. Reducing the makespan can merge the time slots of different traffic with the same priority as much as possible, which can obtain more compact scheduling results and improve bandwidth utilization [23]. In addition, minimizing the worst end-to-end delay can effectively reduce the upper bound of the transmission delay of each TT flow, which can be expressed as

$$l_{all.e2e} = \min \max_{f_{i,j} \in f_i} (D_{i,j,e2e}) \quad (10)$$

After the normalization operation, the total optimization function is defined as:

$$l_{all} = \min \left[w \tilde{l}_{mspan} + (1 - w) \tilde{l}_{all.e2e} \right] \quad (11)$$

where $w \in [0, 1]$ represents the optimization weight, \tilde{l}_{mspan} and $\tilde{l}_{all.e2e}$ are normalized values, respectively.

3. Joint Routing and Scheduling Optimization Strategy Based on APM-GA.

To achieve deterministic low-latency transmission in TCN, a joint routing and scheduling optimization method is proposed. As shown in Figure 2, the framework consists of TT flow prioritization, routing path selection and scheduling optimization. TT flows with larger frame sizes and shorter periods occupy more bandwidth and are more difficult to schedule, so TT flows with higher priority should be firstly scheduled. Scheduling priority can be expressed as

$$f_k \cdot u = \frac{f_k \cdot S}{f_k \cdot T} \quad (12)$$

Based on K-shortest paths and the inter-flow conflict degree, a candidate path set is established, which can avoid scheduling failures caused by time slot conflicts on shared paths. An adaptive population migration genetic algorithm (APM-GA) is designed to optimize makespan and worst end-to-end delay. If no feasible schedule is found with the current path, the next path in the candidate set is evaluated.

3.1. Routing method based on K-shortest path and inter-flow conflict degree.

In TSN, the shortest path routing method is typically used, but it will lead to load imbalance and congestion on certain links, which will increase delay and packet loss. To minimize conflicts among TT flows, the K-shortest path algorithm is used to generate up to p candidate paths R_k for each TT flow f_k . Candidate paths that exceed the end-to-end delay deadline $D_{k,e2e} < f_{k,dll}$ are discarded. Among the remaining candidates, inter-flow

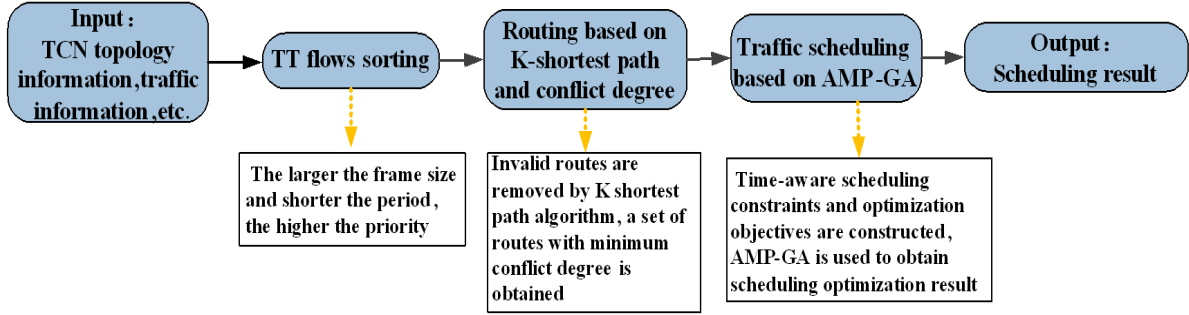


FIGURE 2. The flowchart of the proposed joint routing scheduling optimization method

conflict degree is calculated based on shared link count, frame size, and period [24], which can be expressed as

$$H(f_i, f_j) = |r_i \cap r_j| \frac{f_i \cdot s \cdot f_j \cdot s}{f_i \cdot T \cdot f_j \cdot T} \quad (13)$$

where $|r_i \cap r_j|$ indicates the number of shared links between the i and j TT flows. The inter-flow conflict degree is characterized by three conflict metrics: the number of shared links, the frame size, and frame period. The lower the inter-flow conflict degree, the lower probability a collision is to occur. The selected route for each TT flow minimizes its conflict degree with other flows. Therefore, during route selection, the i th TT flow should select the path with the minimum inter-flow conflict degree $\min(H(f_i, f_j))$, which can effectively avoid inter-flow conflict and make it easier to obtain feasible solutions for scheduling algorithm.

3.2. APM-GA algorithm. Genetic algorithm is a meta-heuristic random search method based on the evolution of the biological world by natural selection, which has the advantages of simple use and strong adaptability. According to the characteristics of traffic scheduling problem in train communication network, each chromosome represents a feasible traffic scheduling solution, and the population is composed of several different chromosomes. Through genetic operations such as selection, crossover and variation, the optimal or approximate optimal scheduling solution is finally obtained. The encoding method adopts the encoding method based on the TT flow transmission process. All TT flows are arranged in different transmission sequences to form each chromosome, and the number of TT flows appearing in a chromosome is related to its own cycle. The selection rules of tournament selection and optimal individual preservation are adopted to select excellent individuals from the previous generation population as the parents for cross-operation. The crossover operator based on process priority is adopted to ensure the inheritance and feasibility of the offspring. The individual mutation operation selects a two-point exchange mutation, which will randomly select two positions of the gene and then change them.

In genetic algorithms, population initialization has a great impact on algorithm optimization effect and convergence speed. An adaptive population migration genetic algorithm is designed for traffic scheduling in train communication networks. To create an initial population of higher quality individuals with genetic potential, two initial population generation strategies based on random sequence (RS) and scheduling priority preference sequence (SPPS) are adopted. Among them, RS strategy randomly generates the initial population, and SPPS strategy obtains the ordered initial population according to the scheduling priority calculated by Formula (12). To realize the cooperative optimization of two populations, the worst solutions of two populations are replaced to the optimal

solutions of each other after each round of independent evolution, so as to avoid the single population falling into the local optimal and accelerate the algorithm convergence process.

It is necessary to increase crossover probability and mutation probability for individuals with poor fitness performance in the early evolution of a population, so as to improve the global search ability and avoid falling into the local optimal trap. As the number of evolutionary rounds increases, crossover probability P_c and mutation probability P_m adaptive adjust within the set probability range:

$$P_c = \begin{cases} \frac{(P_{\max.c} - P_{\min.c})(f_c - f_{\max})}{f_{\max} - f_{mid}} & f_c \geq f_{mid} \\ P_{\min.c} & f_c < f_{mid} \end{cases} \quad (14)$$

$$P_m = \begin{cases} \frac{(P_{\max.m} - P_{\min.m})(f_m - f_{\max})}{f_{\max} - f_{mid}} & f_m \geq f_{mid} \\ P_{\min.m} & f_m < f_{mid} \end{cases} \quad (15)$$

where f_{\max} and f_{mid} are the maximum and median fitness of the population, f_c and f_m are the larger fitness of two crossover individuals and the fitness of mutant individuals, and $P_{\min.c}$ and $P_{\min.m}$ are the minimum crossover and mutation probabilities, respectively, to avoid falling into local optimal prematurely.

The process of APM-GA is shown in Figure 3, which mainly includes the following steps:

1) The initial parent population R_1 with the chromosome number N_{all} is randomly generated, and the same number of initial parent population R_2 is generated according to scheduling priority preference sequence;

2) The initial parent populations R_1 and R_2 were selected and cross-mutated to generate progeny populations, and the parent progeny populations were merged to obtain the evolved populations R_1^i and R_2^i ;

3) The fitness of R_1^i and R_2^i populations was calculated in the i th iteration and sequenced respectively;

4) Remove the worst solutions in R_1^i and R_2^i , respectively, and transfer the optimal solution of each population between the two populations, and we can form the next-generation parent population in R_1^i and R_2^i ;

5) If the maximum number of iterations is not obtained, the crossover probability and mutation probability of different populations are adaptive adjusted, and the child populations are generated by the selection and cross-mutation operations of populations R_1^i and R_2^i , respectively. The child population and parent population are merged to get the evolved populations R_1^{i+1} and R_2^{i+1} , respectively. Steps 3) and 4) are repeated.

6) If the maximum number of iterations is reached, the optimal solution of the two populations is compared to obtain the final scheduling solution.

4. Experimental Results and Analyses.

4.1. Experimental setting. NetworkX is a graph theory and complex network modeling tool developed in Python language, which has strong flexibility and scalability. In this paper, NetworkX simulation tool is used to build a train communication network model. A TCN ring network is constructed as the network topology in the simulation experiment, which includes 8 switch nodes and 25 terminal nodes, and the network simulation model is shown in Figure 4. The network traffic data information is shown in Table 1, the link transmission rate is set to 100Mbps, the link propagation delay is equal, and the relevant settings are in accordance IEC 61375 standards. The number of TT flows is set between 0 and 500 to simulate different application scenarios of TCN. All algorithms were

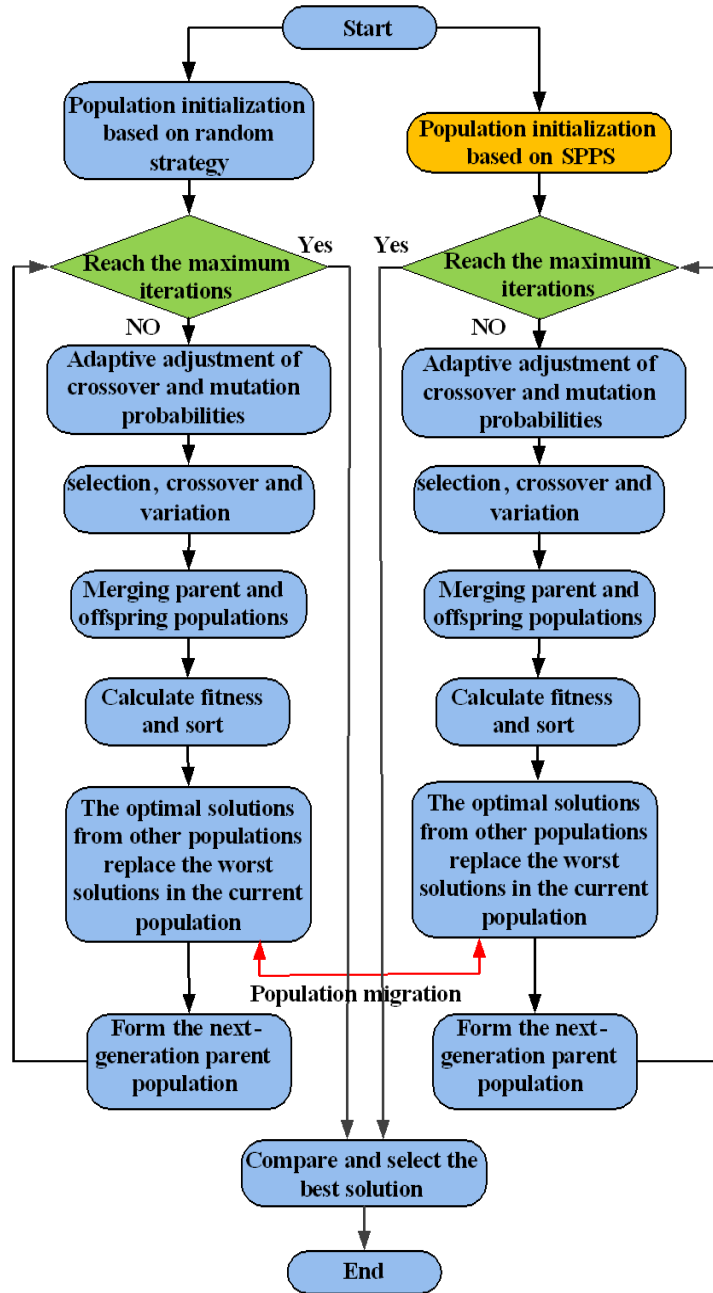


FIGURE 3. The optimization process of APM-GA

implemented in Python3.8, the operating system is Windows11, the computer processor is Intel i5-8400 with the 2.8GHz main frequency and 16G RAM.

To verify the superiority of the proposed scheduling optimization algorithm, tabu search (TS) algorithm, ant colony optimization (ACO) algorithm and genetic algorithm (GA) were selected as comparison optimization algorithms. The proposed APM-GA algorithm consists of 2 populations, the number of each population is 100, the maximum and minimum crossover probabilities of each population are 0.9 and 0.6, the maximum and minimum mutation probabilities are 0.3 and 0.1, respectively. The Tabu tenure is 100 and the maximum iteration is 150. The number of ants and initial levels of pheromone are 100 and 0.8, respectively, heuristic factor and evaporation coefficient are 3 and 0.5, respectively. The traditional GA includes one population, the number of population is 100, the crossover probability is 0.8, and mutation probabilities are 0.1. All of these methods utilize

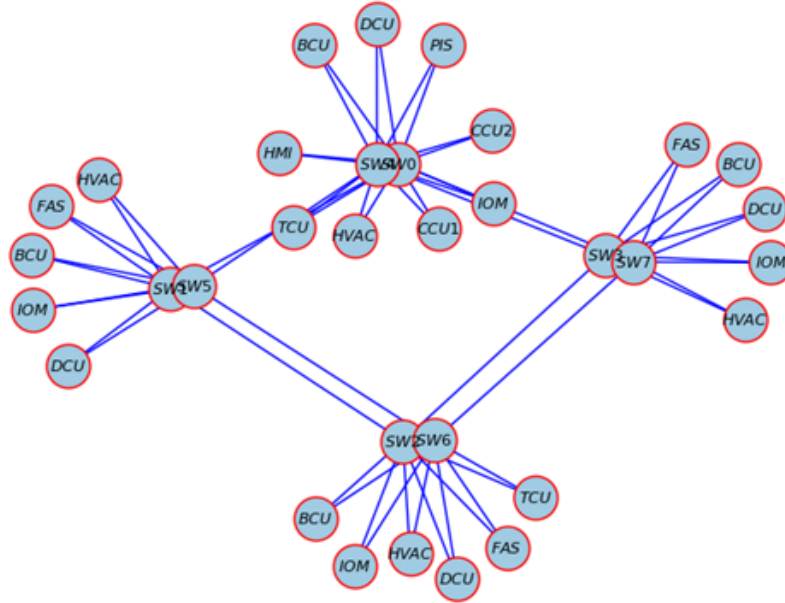


FIGURE 4. Simulation model of TCN ring network

the same optimization function, optimization weight w is set to 0.5, the makespan and the worst end-to-end delay are equally important in the practical application scenarios of TCN.

To verify the superiority of the proposed joint route scheduling method, the traffic scheduling optimization algorithm in this paper is combined with the shortest path routing algorithm (SF+APM-GA) and the load balancing routing algorithm (LB+APM-GA) respectively as two comparison algorithms. In addition, two advanced joint scheduling methods are selected as the comparison methods, which include ILP-based joint routing and scheduling method (ILP-JRS) [17] and constraint programming-based joint routing and scheduling method (CP-JRS) [18].

4.2. Optimization performance validation. The convergence curves of different scheduling optimization algorithms are shown in Figure 5. The smaller the fitness, the better the optimization effect. Compared with other classical optimization algorithms, the

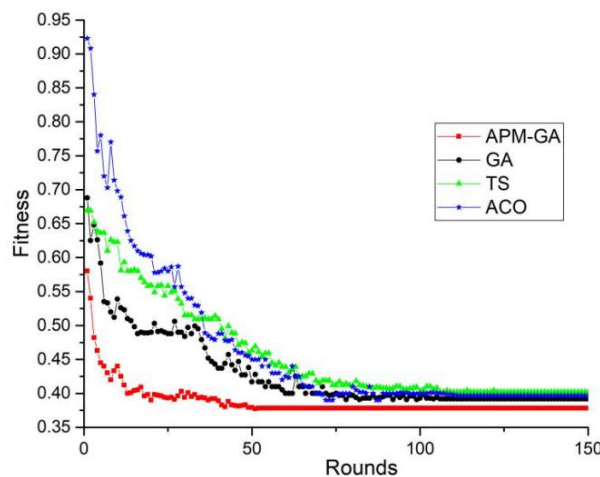


FIGURE 5. Convergence curves of scheduling optimization algorithms

APM-GA optimization algorithm proposed in this paper has the fastest fitness convergence in the first 50 rounds. The fitness of APM-GA optimization algorithm basically converges after the 50th round, while other classical optimization algorithms reach convergence after the 100th round. APM-GA algorithm has the lowest convergence fitness and the best scheduling optimization performance, which improves 7.5% compared with the traditional GA algorithm, and 11.9% and 14% compared with the ACO and TS algorithms, respectively. The experimental results show that APM-GA algorithm has strong searching ability and can obtain better scheduling optimization solution.

The scheduling success rate is an important indicator of the performance of joint scheduling method. The higher the scheduling success rate, the greater the schedulability enhancement achieved by the scheduling method. Different numbers of TT flows reflect different network load conditions, and the numbers of TT flows are set as 50, 100, 150, 200, 250, 300, 350, 400, 450 and 500, respectively. The scheduling success rate of the joint scheduling method under different numbers of flows is shown in Figure 6(a). Compared with other scheduling methods, the scheduling success rate of the proposed method remains 100% within 300 TT flows and can still reach 84% when there are 500 TT flows, which indicates that the proposed method has ability to route and schedule each TT flow

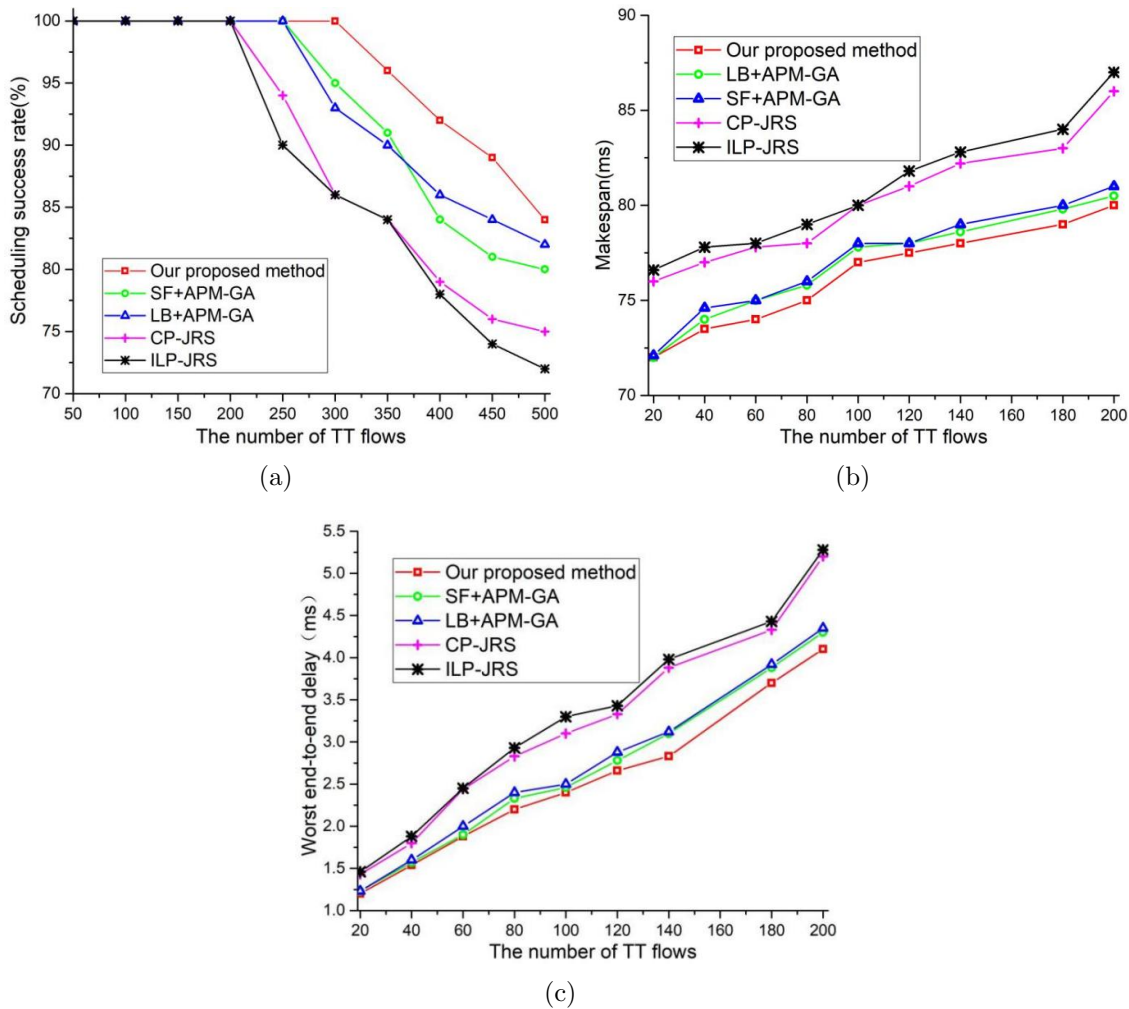


FIGURE 6. Comparative experiment results: (a) Scheduling success rate of different JRS methods; (b) makespan of different JRS methods; (c) worst end-to-end delay of different JRS methods

and effectively expand the search space for joint scheduling, and it is easier to obtain scheduling optimization solution. The route selection of SF+APM-GA and LB+APM-GA methods is single and does not consider inter-flows conflict. Therefore, as the number of TT flows increases, the scheduling success rate of these methods is always lower than that of the proposed method when the number of TT flows reaches 250. The scheduling success rate of CP-JRS and ILP-JRS can maintain 100% in small-scale networks with less than 200 TT flows. However, as the number of TT flows continues to increase, the probability of inter-flow conflict increases, and the scheduling success rate of the two methods decreases significantly, which has limitations in large-scale network.

Makespan and worst end-to-end delay are two real-time performance metrics that reflect the optimization performance of different scheduling methods. The lower the metrics, the better the scheduling effect. In the event of flow scheduling failures occurring, real-time performance metrics would be substantially compromised, consequently rendering comparative evaluations of different scheduling methods meaningless. Therefore, the real-time performance is compared on the premise of successful scheduling, so the number of TT flows is set to less than 200. 200 TT flows are fully capable of meeting the transmission requirements in metro train for time-sensitive data, including train control commands and equipment condition monitoring. The performance comparison results of the joint route scheduling method are shown in Figure 6(b) and Figure 6(c). Compared with other scheduling methods, the proposed method has the lowest makespan and worst end-to-end delay under different numbers of TT flows, which indicates that the TT flow scheduling result is more compact and the delay upper limit is lower. In addition, according to IEC 61375, the period is set to be 2^n times the smallest period, the hyper-period does not become significantly large, so the makespan remains similarly unaffected. Our method can ensure the deterministic transmission of TT flow with high quality and low delay, and can effectively reduce the number of corresponding guard bands. Moreover, it also provides more time slots for non-periodic and non-real-time data such as message data, streaming data and best-effort data.

5. Conclusions. To achieve the high reliability and low delay of deterministic communication in the next generation TCN, a joint scheduling method is proposed, the TCN network topology and traffic model are constructed, routing candidate path set is obtained based on the shortest path and inter-flow conflict degree. The makespan and the worst end-to-end delay are considered as optimization objectives, and a scheduling optimization algorithm based on APM-GA is designed, two initial populations are generated through random strategy and scheduling priority sequence strategy, and crossover and mutation probabilities according to different scheduling conditions are adaptively adjusted, which can effectively improve the convergence speed and optimization performance. Experimental results show that the proposed method is superior to other traditional methods in three scheduling performance metrics. In the future, deep reinforcement learning algorithms will be investigated to solve the joint scheduling problems in TSN. In addition, to verify the superiority of the proposed optimization algorithm, future work will expand the scope of application scenarios, such as in-vehicle network and Industrial Internet of Things.

Acknowledgment. This work is supported by China State Railway Group Co., Ltd. Science and Technology Research and Development Program Project (P2023J001). The authors also gratefully acknowledge the helpful comments and suggestions of the reviewers, which have improved the presentation.

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