Real-time Railway Transit Management Based on Multi-Agent System (MAS)

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Abstract. Because of environmental concerns, increasing attention has been given to developing energy-efficient technologies. As an essential public transportation method, metro transit is facing increasing pressure. Disturbances may cause the offline-optimized timetable and speed trajectory to be invalid. The present paper proposes a multi-agent system (MAS) train control method, in which each train is controlled by an agent. Each train agent has a simulation platform and an optimization platform. The simulation platform collects information such as track slop, speed limitation, speed trajectories of neighboring trains from a few neighboring agents. The simulation platform sends a signal with the collected information to the optimization platform when it detects a disturbance. Afterward, the optimization platform performs energy-aimed optimization to the timetable and corresponding speed trajectory based on a combination of a trained Neuro Network and a Mixed Integer Linear Programming (MILP) model. The test result shows an encouraging balance in optimization time and accuracy. The case study result proves that the proposed approach could provide a more energy-efficient control strategy when disturbances occur.

1. Introduction

Metro transportation has the characteristics of safety, punctuality, large capacity, etc. It is an essential mode of transportation in the modern city. The current technology is able to provide a highly optimized timetable and corresponding trajectory to the trains in the metro system through offline optimization. However, when a disturbance occurs, the trains may discard the optimized timetable and speed trajectory to ensure safety, which makes the offline optimization invalid. In order to improve the robustness and flexibility of rail transit control, some research paid attention to deploy agent-based techniques in railway fields. However, when a disturbance occurs, the trains may discard the optimized timetable and speed trajectory to ensure safety, thus making the offline optimization ineffective. In order to improve the robustness and flexibility of rail transit control, deploying agent-based technology in railway fields has become a research trend. Burckert et al. proposed an agent-based system that includes a global agent and mobile agent. The developed agents are able to collaborate through communication, and the system provides scheduling support in uncertain and dynamic situations [1]. Blum and Eskandarian proposed a collaboration protocol among agents in 2002 to improve the flow in the rail transit field, and the simulation result shows a 10-fold improvement [2]. Proença and Oliveira proposed a multi-agent system for rail transit, which consists of two layers, a control layer, and a learning layer. The control layer includes three types of agents: Supervisor, Train, and Station. The control layer responsible for regulating safety, fluidity, etc. The learning layer responsible for inferring rules that improve traffic control [3]. Siahvashi and Moavenil proposed a distributed automatic train control system. By
combining Voronoi cooperative systems theory, a fuzzy controller is developed, and adjacent trains are able to avoid colliding. Hassanabadi et al. proposed a decentralized MAS control structure, which includes station agents, train agents, and the center of the traffic control agents [4]. The simulation result illustrated each train in the system is able to make decisions when the corresponding leading train met accident and able to avoid collisions. In 2019, Guo et al. proposed a multi-agent system in rail transit, in which each train is controlled by an autonomous agent. Every train agent ensures safety and reduces kinetic energy loss when a disturbance occurs [5–7]. Based on the proposed structure, Guo et al. integrated a MILP model and a trained neural network to the MAS system in 2020, which enables each train to optimize the timetable and corresponding speed trajectory when a disturbance occurs. Based on the proposed structure, the same team integrated the MILP model and a neural network into the multi-agent system in 2020 [8]. Simulation results in various scenarios show that when a leading train has an accident, all following trains in the system are able to make real-time optimization and generate speed trajectories that ensuring driving safety and reducing energy consumption. Liu introduces a method to realize group intelligence for a MAS system in rail transit based on virtual coupling technology [9]. The simulation result proves the method reduces train operation intervals and improves efficiency.

The present paper proposes a MAS system that adopts an improved train agent (compare with the train agent that is adopted in the MAS system illustrated in [8]). The improved train agent includes a simulation platform and an optimization platform. The combination of the two platforms enables each train agent to continuously exchange information with the environment and collect the data for further analysis.

2. Proposed Methodology

2.1. MAS Framework

The proposed system includes three types of agents: Train Agent, Station Agent, and Central Agent. Figure 1 shows the communication structure of a scene. There are three trains running among three stations in the scene, and the positions of the three trains are shown in the figure below.

![Figure 1. Structure of the MAS system.](image)

Train Agents 1 to 3 are the agents controlling the corresponding trains. All agents have communication channels with the environment. For instance, Train Agent 1 exchanges information with the Central Agent, Station C Agent, Train Agent 2, and Train 1 Driver. When a disturbance occurs, Train Agent 1 sends signals to the neighboring agents that may be affected. Train Agent 2 then discovers whether the disturbance affects normal travel. The agent will generate a new timetable and corresponding trajectory if it found the offline optimized timetable and speed trajectory no longer satisfy
safety requirements governed by the moving block system (MBS). Station Agents receive the signal from agents of the upcoming train to update arriving time. Central Agent is responsible for helping the other agents to exchange information when they meet troubles to exchange information (such as communication failed due to weak signal strength).

2.2. Train Agent

The adopted train agent is shown in figure 2. Each train agent includes a simulation platform and an optimization platform. The simulation platform collects information from the environment, such as the speed trajectory of neighboring trains, passenger flow, boarding time. When a disturbance occurs, the simulation platform calculates the movement authority according to the moving block system and speed trajectory of neighboring trains. Afterward, the simulation platform forms constraint equations and sends them to the optimization platform. Then the optimization platform performs timetable and trajectory optimization subsequently.

![Diagram of the proposed control framework.](image)

Figure 2. The proposed control framework.

The proposed system has a hybrid triggering mechanism that combines time triggering and event triggering. Assume Train(i-1), Train(i), and Train(i+1) are three neighboring trains running on a track and controlled by three individual agents. Train(i-1) is the leading train, Train(i) is the middle train, and Train(i+1) is the following one. Figure 3 shows the time triggering mechanism of Train(i) Agent. Train(i) Agent receives signals from a few stations that are about to arrive and neighboring trains every \( t(i) \) seconds to update the environment states. If a disturbance is detected, Train(i) discovers whether the disturbance will influence travel safety. The speed trajectory of Train(i-1) and Train(i+1) is received and used to check whether the minimum distance satisfies safety requirements (which is given based on moving block system, or MBS in short). If the safety requirement is satisfied, Train(i) Agent then generates constraint equations and sends them to the optimization platform. Otherwise, Train(i) needs to decelerate to stop and wait for the updated information from the environment. When the updated information is received, Train(i) Agent then generates and sends constraints to the optimization platform.
The principle of the adopted MBS is shown in figure 4. Leading train and following train exchange information during travel. At any time when the two trains are running, if the following train stops at the deceleration of service braking, the distance between the location where the following train completely stops and the position of the leading train should be further than a predefined safe distance.

![Figure 3. Time Triggering process for Train(i).](image)

The optimization platform includes timetable optimization and trajectory optimization. The timetable optimization is realized by a trained neural network, and the trajectory optimization is realized by a
MILP model. The procedure is similar to the system proposed by [8], and due to space constraints, it is not described in detail here.

3. Case Study

This section provides a case study to test the proposed train agent. Three trains travel between two stations (Stations A to B) with a speed limit of 30 m/s. The distance between the two stations is 3 km. The mass of the trains is 230 tons, and the total travel time is 290 seconds. Train 1 (the leading train) travels properly in the beginning and meets a disturbance at 100 seconds. In the scenario with the proposed MAS system, Train Agent 1 receives the signal from the Train 1 Driver. The signal includes information showing that Train 1 needs to take a temporary stop and is expected to reaccelerate at 180 seconds, then Train Agent 1 sends the signal to Train Agent 2. Based on the calculation, Train Agent 2 found the predetermined speed trajectory does not satisfy the MBS requirements. Thus an optimization procedure is carried out. The new speed trajectory of Train 2 is sent to Train Agent 3, and it is found the planned speed trajectory of Train 3 still satisfies MBS safety requirements. Thus, Train 3 travels by following the original trajectory. The adopted speed trajectories of the three trains are shown in figure 5a. In the comparison scenario (figure 5b), Train 2 follows the predetermined speed trajectory and decelerates at the position that the distance between Train 1 and Train 2 no longer satisfies MBS requirements. Then Train 2 decelerates to stop until Train 1 solves the problem and reaccelerates.

By comparing the energy consumption of the two scenarios, it could be found that the proposed system and train agent is able to reduce energy consumption significantly when a disturbance occurs. Based on hundreds of tests, the proposed system usually provides an optimized speed trajectory in a personal laptop within a few seconds, which satisfies the real-time optimization demand in practice.

4. Conclusion

A train agent composed of two platforms is proposed, one for simulation and the other for optimization. Train agent exchanges information with the environment through the simulation platform. When the platform detects disturbances, it will automatically generate the constraint functions and send it to the optimization platform. Based on a MILP model, the optimization platform is able to support energy-aimed optimization and sends the optimized trajectory among multiple stations back to the simulation platform. Afterward, the simulation platform sends the new trajectory back to the environment, where other neighboring agents receive the updated information. In the case study, the proposed system provides optimized speed trajectories when a disturbance occurs in several seconds, which shows excellent efficiency. It is planned to test the system in more cases to further verify the efficiency of the system and to realize group intelligence among multiple trains based on the prototype provided.
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