Coordinated Route Recommendation for Improving Social Distancing in a Congested Subway Network

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Abstract: We investigate the problem of providing coordinated route recommendations to subway passengers to reduce peak-hour congestion and improve social distancing during a pandemic such as COVID-19. We develop TransMARL, a model-free method that combines multi-agent reinforcement learning and curriculum learning to learn optimal routing policies by interacting with the environment. Furthermore, TransMARL is simple in design and adapts the framework of centralized training with decentralized execution. Applying TransMARL to the busy Taipei Metro network with more than 2 million daily ridership, our simulation result shows that overcrowded passengers can be reduced by more than 50% with less than 10 minutes increasing traveling time when 20% or more passengers follow the provided route guidance. The result outperforms previous well-known transit assignment methods, e.g., the all-or-nothing and stochastic user equilibrium.

1 INTRODUCTION

As the population grows, the number of people on the road during peak hours increases, and crowding in public transport is inescapable. Studies have found that overcrowding induces travel delays and negatively affects passengers' well-being, including increased anxiety, stress, and exhaustion (Tirachini et al., 2013). During the outbreak of pandemic, such as the COVID-19 pandemic, riding a densely packed vehicle could also increase infection risk. Even though there was a significant drop in ridership during the outbreak, the risk of contagion could be escalated once ridership rebounded to normal. Consequently, finding a strategy to reduce overcrowding is necessary (Teixeira and Lopes, 2020). Furthermore, even if the ridership stays low, the crowding problem during peak hours is inevitable.

While it is impossible to eliminate congestion entirely, its effect can be reduced by various policy measures. Several approaches to relieve congestion in public transport have been studied. Early bird ticket strategy, where passengers were offered free tickets for trips completed before 7 A.M. was implemented in Melbourne rail system (Currie, 2010). In some large metro stations in China (Beijing, Shanghai, and Guangzhou), a station inflow control scheme is employed to limit the number of passengers waiting at the platform, purchasing area, and ticket gates (Zou et al., 2018). Real-time crowding information was provided in the Stockholm metro to encourage passengers to board less crowded vehicles, thus leading to a more uniform passenger load distribution (Zhang et al., 2017).

Finding a feasible policy to reduce the time spent on highly packed vehicles is a significant challenge as transit overcrowding is more than planning and overpopulation; it also includes behavior prediction and adaptation. To help estimate the distribution of passengers and validate the effectiveness of diverse policies, transport planners and researchers employ transit assignment models. These models take an origin-destination (OD) matrix of passenger demand and a transit network as input, estimate the travelers' choices of route, and then generate aggregate ridership statistics as output. The output can then be used to assess the effectiveness of a particular policy and the overall performance of the transit network.

Most transit assignment models are built based on user equilibrium conditions (Wardrop, 1952), in which no traveler can improve his/her perceived utility cost by switching routes. However, its static char-

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acteristic is criticized as inapplicable to the networks with time-varying OD demands. Moreover, the conventional equilibrium model is structurally incompatible with observed user behavior, namely user route choices habits, random variations in demand and network conditions, as well as transient effects (Cascetta and Cantarella, 1991). A better approach is to emulate the process leading to equilibrium instead of solely finding a fixed point. Therefore, to model each agent's decision-making process at each stop and to better understand passengers' behavior, we propose to use an agent-based model. Furthermore, to find effective policies and strategies, we also incorporate a learning-based model.

We implement a learning approach based on a policy gradient variant of reinforcement learning (RL) called PPO (Schulman et al., 2017). We first formulate the transit assignment problem as Markov games (Littman, 1994), where each agent's observation is a 2D representation of the agent's surrounding area, and the action is to board or alight the train.

The organization of this paper is as follows. Section 2 provides a detailed formulation of the underlying problem, including network representation, simulation framework and path allocation model. Section 3 describes the methodology used, which consist of multi-agent actor-critic, model architecture and curriculum learning. In Section 4, we present Taipei subway network dataset, experimental settings and training parameters. Section 5 shows the result of our experiments and discussion and further analysis. Finally, in Section 6 we give a summary of this work as well as our conclusion.

2 PROBLEM FORMULATION

2.1 Network Representation

We consider a transit network consisting of a set of distinct lines and stations. A line is a group of stations that passengers can transit with the same train, and stations are the place where passengers board and alight vehicles. The transit network is represented as a graph $G = (N, \bar{E})$ where the node set N represents stations and directed edges set $\bar{E}$ represents network links. There are two kinds of edges:

1. In-vehicle travel edge, corresponding to a route between two adjacent stations.
2. Walk edge, corresponding to a link between two adjacent transfer stations.

Each directed edge e_{ij} from n_i to n_j is associated with a travel cost c_{ij} which corresponds to the time travelings from n_i to n_j.

E_s is defined as the set of transit paths on route section s and s is a route section between passenger's origin node n_O to destination node n_D. The expected travel time from origin to destination is defined as:

$$T(n_O, n_D) = W_{\bar{E}_s} + V_{\bar{E}_s} + K_{\bar{E}_s}, \quad (1)$$

where $W_{\bar{E}_s}$ is the expected waiting time, $V_{\bar{E}_s}$ is expected in-vehicle time, and $K_{\bar{E}_s}$ is expected walking time.

Only common/attractive lines are considered in this study. $\bar{E}_s$ represents a set of attractive lines that consists of paths with expected time delay less than or equal to a given constraint. More formally,

Definition 2.1 (Attractive path)**.** A path $P(n_O, n_D) \in E_s$ is an attractive path if $T(n_O, n_D) \leq \delta T^*(n_O, n_D)$.

where $T^*(n_O, n_D)$ is the minimum travel time and $\delta = 2$.

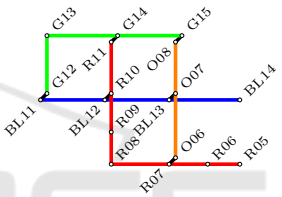


Figure 1: Illustration of a sample network.

Figure 1 provides a schematic chart illustrating the attractive lines notion used in this study. A passenger whose origin is at node BL11 and destination at node R05 would only consider two different routes, specifically (BL11 - BL12 - R10 - R09 - R08 - R07 - R06 - R05) and (BL11 - BL12 - BL13 - O07 - O06 - R07 - R06 - R05). Three other routes (BL11 - G12 - G13 - G14 - R11 - R10 - R09 - R08 - R07 - R06 - R05, BL11 - G12 - G13 - G14 - R11 - R10 - BL12 - BL13 - O07 - O06 - R07 - R06 - R05 and BL11 - G12 - G13 - G14 - G15 - O08 - O07 - O06 - R07 - R06 - R05) that traverse through the green line are not considered attractive.

2.2 Simulation Framework

The agent-based approach to transit assignment simulates the dynamics of vehicles and travellers in the transit system and yields the temporal and spatial distribution of the later over the former. A modelling framework for emulating transit dynamics is presented in Figure 2. The dynamic representation of a public transportation system involves two primary agent categories: vehicles and travellers.

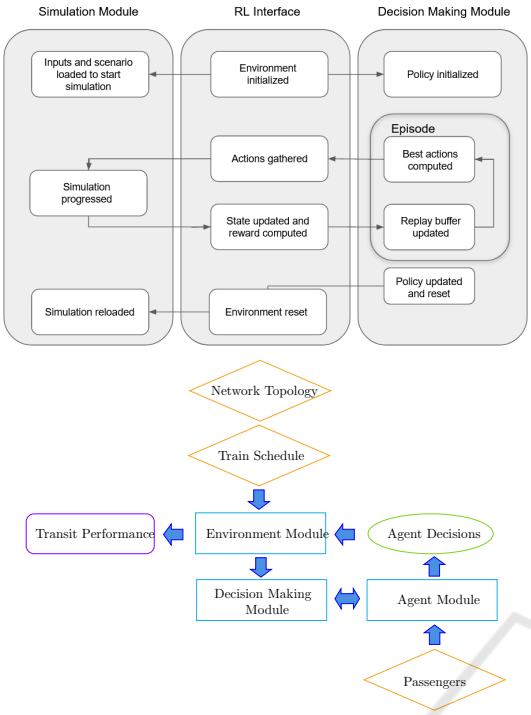


Figure 2: Framework for multi-agent transit operations and assignment model. The above part shows the three main modules and the below part shows the interactions among these three modules.

In Figure 2, There are three main modules: simulation module, RL interface and decision making module. The simulation module holds the underlying subway network and controls the operation of the trains. This module takes network topology, train schedule and its attributes, along with travel itinerary of each individual passenger as inputs. It initializes the simulation environment and then passes initial state to interface module. Upon receiving all passengers' action from interface module, it applies all of the actions on environment, progresses to the next state, and passes the new state to interface module. When the reset command is given, all trains and agents are returned back to their origin position. A simplified algorithm is provided in Algorithm 1.

The RL interface module handles the interaction and message passing between simulation and decision making modules. This module also acts as an entry point to interact with the whole framework. At first, the environment is initialized, which in turn starts the simulation and initializes policy network. After the initialization is finished, initial state is passed to decision making module. At each time step, actions for guided agents are collected from decision making module and greedy actions for unguided agents are retrieved from a pre-computed table. These actions are then passed to simulation module. Subsequently, the updated state and reward are sent to decision making module to be processed. When an episode is over, a signal is sent to reset both simulation and policy modules. In addition, statistics are accumulated to measure the performance of current policy.

The decision making module first initializes the policy with random parameter or parameter learned from previous learning stage. At each time step, it computes an optimal action for each agent based on its observation and current best policy, then stores a tuple of states, actions, rewards and next states in the replay buffer. When terminal state is reached, policy is updated according to cumulative reward and the environment is reset. Basically, this module learns a strategic policy to minimize overall congestion from both trains and agents spatial distribution.

Algorithm 1: MRT Simulator.

```
SetAlCapHSkip0cm
input : network topology, train schedules,
        passengers' itinerary
Initialize train and agent states
for t ∈ T do
    Get all trains R that arrive at time t
    for r ∈ R do
        Get actions for all passengers
        Apply the chosen actions
        Update state of train r
    end
end
```

2.3 Path Allocation Model

2.3.1 User Classes

In a situation where route recommendation is provided to passengers, at least two user classes are defined: those who follow the guidance and those who do not follow the guidance (Van Vuren and Watling, 1991). Each of these user classes would have a different perception and behavior that lead to different route choices. The guided agents completely follow the route recommendations given by our trained model, while unguided agents follow a greedy policy. Consequently, unguided agents always board the first incoming vehicle with the shortest total travel time, regardless of the congestion level.

2.3.2 Observation Space

We consider a partially-observable discrete grid-world, where agents can only observe the state of the

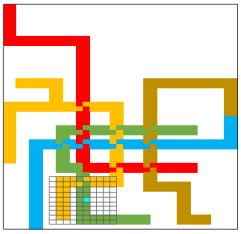


Figure 3: Observation space for each agent. The grid cells around the cyan grid denote the region that can be observed by those agents within the cyan grid.

world in a limited view centered around themselves in a 10x10 grid. We assume a fixed observation space can allow the policy to generalize to arbitrary world sizes and also helps to reduce the input dimension to the neural network. In this limited observation, we separate the available information into different channels to simplify the agents' learning task. Specifically, each observation consists of matrices representing the position of trains, position of other agents, and the agent's own goal location within the 10x10 window (see Figure 3). Additionally, we also give information about agent's travel itinerary, such as the coordinate of origin, the coordinate of destination, the shortest time to arrive at destination, number of passengers at current station, the number of passengers on the current train, station ID, train ID, as well as the estimated traveling time. To encode agent's identity, agent ID is appended to its itinerary features.

2.3.3 Action Space

In the original transit assignment problem a passenger chooses a specific path from the set of attractive routes. To allow more flexible path choices, instead of selecting a fixed path prior to departure, we are modeling passenger's decision making process on the way when s/he travels. When passengers start from their origin the exact path they use is neither known nor decided upfront. The agent takes each action decision based on the hidden mental model that evaluates all of the attractive routes.

At each stop, passengers have two choices, whether to board the train or wait for the next train. When passengers are on the train and the particular train is at a stop, they can choose to stay or alight the train. At each time step, only 2 actions are valid, so we masked out invalid actions. We experimentally observed that this approach enables more stable training, compared to giving negative rewards to agents for selecting invalid moves. Additionally, to combat the problem of getting oscillating policies on the way to convergence, agents are prevented during training from returning to the station they visited before. This is necessary to encourage exploration and to learn effective policies.

We implement a queuing mechanism to imitate the actual boarding process where each agent's boarding priority is based on his arrival time at the current stop. Accordingly, when a vehicle is at full capacity and no boarding action is possible, agents with later arrival time are denied boarding. This leads to increased waiting time and influence agent's path choice.

2.3.4 Reward Structure

Our reward function follows the same intuition that most reward functions for gridworlds use, where agents are punished for each time step they are not arriving at the destination, leading to the strategy of reaching their goals as quickly as possible.

To reflect the passenger comfort and crowding levels within the transit vehicle, agents are given a re-routing penalty according to the average area per person in the car (m^2/person). Four crowding levels (b) are used for this measure, ranging from comfortable ($\geq 0.83 m^2$/person), normal ($(0.83, 0.47] m^2$/person), slightly packed ($(0.47, 0.28] m^2$/person), and packed ($< 0.28 m^2$/person) (Weng, 2020). The re-routing penalty is calculated as a step-wise function. A constant amount of penalty c is given for the comfortable and normal crowding levels, while crowding penalty proportional to the multiplication of the level of crowdedness ($\frac{1}{b}$) and duration of traveling (t) is given for slightly packed and packed crowding levels. It is calculated as follows where b is agent's current area in m^2:

$$P_1 = \begin{cases} -\frac{1}{b} \times \frac{t}{\max_{i \in N} t_i}, & \text{if } b < 0.47 \\ -c, & \text{otherwise} \end{cases} \quad (2)$$

We penalize agents slightly more for staying still than for moving, which is necessary to encourage exploration. Agents are penalized for not boarding incoming train and wait at the stop station. The amount of penalty given is a linear function of the waiting time in seconds. It is calculated as follows where w_i the waiting time at current stop and a_i is agent's action at time step i:

$$P_2 = \begin{cases} -w_i, & \text{if } a_i = \text{wait} \\ 0, & \text{otherwise} \end{cases} \quad (3)$$

Agents are also penalized for doing cross-platform interchange. The amount of penalty given is a linear function of the walking time in seconds (k). It is calculated as follows where k_i is the walking time at current stop and s_i marks the current station:

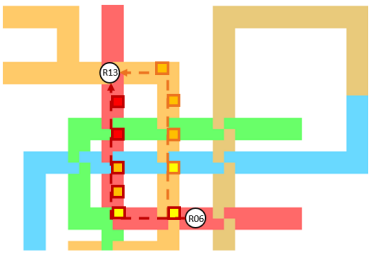


Figure 4: Illustration of alternative route.

$$P_3 = \begin{cases} -k_i, & \text{if } s_{i-1} = s_i \\ 0, & \text{otherwise} \end{cases} \quad (4)$$

The total reward is calculated as linear combination of waiting penalty and re-routing penalty. Its formula is given by

$$r = \alpha P_1 + \beta P_2 + \eta P_3, \quad (5)$$

where α is weight of re-routing reward, β is weight of waiting reward, and η is weight of walking reward:

2.4 Use Case

We consider a route planning and navigation system such as Google Maps[1] and Waze [2], where users are given a routing plan for their trip. However, in this work the locations are limited to subway stations. Each user requests for a trip using an application on a mobile client. The application asks the user to input a starting station, a destination station, the date and the starting time of trip. The input data is processed, then an efficient route from the origin to destination station and an estimated time of arrival (ETA) are provided.

2.4.1 Alternative Route

The application will recommend an alternative route that might be longer than the shortest path, but has lower crowding level in general. Consider the scenario illustrated in Figure 4, which shows a user who wants to travel from R06 to R13. There are two attractive paths to reach R13 from R06 marked by dashed line. The dark red line indicates the shortest path, whereas the dark orange line indicates an alternative path. Along the path, the current crowding condition at each station is shown. The train color represents crowding condition, red for packed, orange for slightly packed, yellow for normal and green for comfortable.

It can be seen that there are two normal, two slightly packed and two packed trains along the shortest path. As for the alternative path, there are two normal and three slightly packed trains. It is obvious that the crowding level of orange line is better than red line. However, if the user were to follow the alternative path, s/he would have to transfer at station R07 to orange line, which results in longer travel time. By comparing the crowding level and the travel delay incurred, our system recommends the dark orange path to the user. It should be noted that our recommendation system will not suggest the user to board or alight at stations different than the inputted data.

2.4.2 Coordination

In real-world scenario, the demand to travel from the same OD pairs would be high. Following the previous scenario, let's assume that the demand to travel from station R06 to R13 is 300. Considering the crowding condition in Figure 4, assigning dark orange path to all passengers would only create a new congestion on the alternative path. To avoid this, our system will try to distribute the passengers so that the overall crowding time is minimized by giving different routing recommendations. For instance, 200 passengers are assigned to alternative path and 100 passengers are assigned to shortest path.

Table 1: Illustration of train schedule at station R06.

Time	Train	Destination	Crowding level
08:09	10103	Tamsui	Packed
08:12	10121	Tamsui	Packed
08:15	10137	Tamsui	Packed
08:18	10142	Tamsui	Slightly packed
08:21	10154	Tamsui	Slightly packed

In addition to alternative path, our solution will also optimize each user's departure time. By providing a suggested departure time, users can spend their time at home or office as opposed to waiting or queuing on the platform. As an example, we can see from Table 1 that the first three trains are packed. According to our coordination policy, 10 passengers are assigned to each of the packed trains and 35 passengers are assigned to each of the slightly packed trains.

3 METHODOLOGY

In this section, we develop TransMARL method to solve passengers routing and transit assignment problem.

[1] https://www.google.com/maps
[2] https://www.waze.com/

3.1 Multi-Agent Actor-Critic

Our work relies on Proximal Policy Optimization (Schulman et al., 2017) and adopts the framework of a centralized training with a decentralized evaluation (Lowe et al., 2017). We use deep neural network to approximate the agent's policy, which maps the current observation of its surroundings to the next action to take. Following the framework of Markov games with N agents, each agent learn its own policy $\pi = \{\pi_1, ..., \pi_N\}$ parameterized by $\theta = \{\theta_1, ..., \theta_N\}$. The gradient of agent i's expected return with respect to policy parameters $J(\theta_i)$ is given by:

$$\nabla_{\theta_i} J(\theta_i) = \mathbf{E}_{s\sim p^{\pi}, a_i \sim \pi_i}[\nabla_{\theta_i} log \pi_i(a_i|o_i) Q_i^{\pi}(\mathrm{x}, a_1, ..., a_N)] \quad (6)$$

where $Q_i^{\pi}(\mathrm{x}, a_1, ..., a_N)$ is a centralized Q-value function for agent i. This centralized Q-value function receives the state information x and actions of all agents, $a_1, ..., a_N$ as input. The state x consists of observations of all agents' itinerary information and a global 10x10 array.

The centralized action-value function Q_i^{π} is learned by minimizing the loss:

$$\mathcal{L}(\theta_i) = \mathbf{E}_{\mathrm{x},a,r,\mathrm{x}'}[(Q_i^{\pi}(\mathrm{x}, a_1, ..., a_N) - y)^2], \text{where}$$
$$y = r_i + \gamma Q_i^{\pi'}(\mathrm{x}', a_1', ..., a_N')|_{a_j' = \pi_j'(o_j)} \quad (7)$$

In addition, the replay buffer $\mathcal{D}$ stores experiences of all agents $(\mathrm{x}, \mathrm{x}', a_1, ..., a_N, r_1, ..., r_N)$.

3.2 Parameter Sharing

First, learning agents are partitioned into 10 different groups. The groups are determined based on passenger's origin station. Basically, each line is divided in half. For instance, red line is divided into two segments where stations R01-R14 belong to the first segment and stations R15-R28 belong to the second segment. There are 5 lines considered in this study, so there are 10 groups in total.

To reduce time complexity and speed up the learning process, we assume that passengers in the same group share similar routing strategies and agents in the same group share the same parameters. Accordingly, agents in the same group use and make update to a collective shared policy. Hence, only 10 parameters $\theta = \{\theta_1, ..., \theta_{10}\}$ are learned.

3.3 Model Architecture

The neural network used to approximate agent's policy has multiple outputs, namely the actual policy and value policy to assess the quality of different policies. We use a simple 2-layer convolutional network followed by a fully connected (fc) layer to extract map features and 2-layer fc to extract basic info features as illustrated in Figure 5. Specifically, the two inputs to the neural network - map observation and basic information - are preprocessed independently, before being concatenated half-way through the neural network. The three-channel matrices i.e., $10 \times 10 \times 3$ tensors representing the local observation are passed through two convolutions, followed by a last fc layer. In parallel, the basic info are passed through two fc layer. The concatenation of both of these pre-processed inputs is then passed through the two output layers. The output layers consist of the policy neurons with a softmax activation function, and the value output.

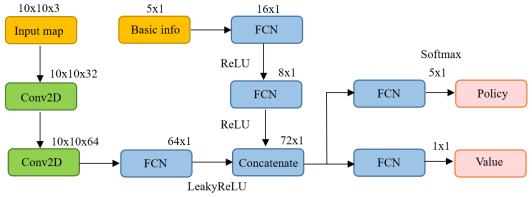


Figure 5: The neural network consists of 2 convolutional layers, followed by a fully connected layer.

3.4 Curriculum Learning

Due to the nature of our environment that has large population, it is hard to trace back the change in the reward signal to each agent. As a result, training takes a long time to converge. A direct training with PPO with 130K guided agents does not yield sensible performance. To address this, we use *curriculum learning* (Bengio et al., 2009) that trains an agent with a sequence of progressively more difficult environments. By varying the number of guided agents, we could control the difficulty level.

We progressively increase the population of guided agents throughout the training process. Particularly, we divide the learning procedure into multiple stages with increasing number of guided agents in the environment. An agent first learn to travel from the origin to its destination in a simpler scenario with less agents and then we leverage these experiences to gradually adapt to later stages with more agents and ultimately our desired population. In addition to enable faster training and guide training towards better region in the parameter space, the purpose of curriculum learning is in line with our multiple user class transit assignment problem. We seek to find the smallest number of guided agents needed to reduce the overall congestion level by training different number of guided agents gradually.

4 EXPERIMENTS

4.1 Datasets

The Taipei subway network considered in this study consists of 5 bidirectional lines with 12 intersections. Passenger-related information were extracted from Taipei MRT AFC transaction data between the year 2017 and 2019 (Department of Transportation, 2019). These transaction records contain information regarding passenger ID, origin station, destination station, entrance time, and exit time. The ridership on a typical weekday is around two million.

The assignment includes 133,097 passengers that recurrently travel during morning peak hours. These travelers are associated with 14,161 different origin-destination pairs and are distributed over more than 600,000 possible paths. The travelers are assumed to depart everyday within the same 15 minutes time window. All trips are generated within 2.5 hours, specifically 1 hour warm-up stage to populate the network with unguided agents, half an hour to distribute all guided agents, and the last 1 hour to let all agents finish their trips.

4.2 Experimental Settings

In our experiment, we applied parameter sharing between agents that share the same origin segment. Each line is divided in half into two line segments, to form 10 different line segments in total. Parameter sharing increases sampling efficiency and thus help the training converges faster. We experiment with different number of guided agents, ranging from 5% to 60% of total population, increased by 5% at a time.

4.3 Training Parameters

Our training procedure is implemented with TensorFlow 2.1.0 (Abadi et al., 2016). We use Adam (Kingma and Ba, 2014) with $\varepsilon = 10^{-3}$ for training. Batch size is 64, discount factor $\gamma = 0.9997$, learning rate $\alpha = 5 \times 10^{-5}$ and the policy entropy 0.01. The model is trained from scratch. The training procedure runs on a machine with Intel Xeon CPU E5-2699v4 at 2.20GHz, and 2 GTX1080 GPUs. The operating system is Ubuntu 18.04. Our final model is trained for around 3 million mini-batches on multiple different scenarios.

Table 2: Penalty across different percentage of guided agents.

Guided agents(%)	Re-route penalty	Wait penalty	Transfer penalty	Total penalty
0	1186.57	5.74	7.27	1199.58
5	1147.91	6.83	7.97	1162.71
10	1119.48	7.25	8.50	1135.23
15	1085.45	10.93	9.38	1105.76
20	1049.61	14.54	10.11	1074.26
25	1036.54	17.67	10.69	1064.9
30	1020.42	20.89	11.27	1052.58
35	1012.09	23.88	11.86	1047.83
40	1001.80	27.08	12.57	**1041.45**
45	1001.84	28.51	12.52	1042.87
50	**1001.25**	31.5	13.14	1045.89
55	1007.03	34.22	13.71	1054.96
60	1021.1	37.04	14.13	1072.27

4.4 Results

4.4.1 Penalty Comparison

It can be seen from Table 2 that re-route penalty decreases as the number of guided agents increases. However, when more than 50% of agents follow the guidance, the performance starts to deteriorate and re-route penalty increases. Similarly, total penalty also decreases as the number of guided agents increases. However, when more than 40% of agents follow the guidance, total penalty starts to increase. Furthermore, both wait penalty and transfer penalty increases as the number of guided agents increases. In other words, while adding more GAs can further improve the level of comfort, the cost or time delay perceived by passengers outweighs the performance gain.

4.4.2 Minimum Number of Guided Agents

Table 3: Travel delay increase and re-route penalty decrease across different percentage of guided agents.

Guided agents (%)	Travel delay (%)	Re-route penalty decrease (%)
10	3.58	5.84
20	7.90	**11.54**
30	11.44	14.00
40	14.72	15.56
50	16.13	15.56
60	19.64	13.88

Table 3 shows that while following route recommendation reduces average re-routing penalty, it also increases average travel time. The increase in average travel time grows linearly with percentage of guided

agents. The average re-routing penalty decreases as the number of guided passengers increases, however, the reduction started to saturate after more than 50% of passengers follow the guidance. It can be seen that the travel delay experienced by 60% of guided passengers outweigh the congestion reduction advantage. The largest re-routing penalty reduction occurs when the number of guided agents is increased to 20%.

The policy's inability to reduce the total travel time could be an indication of Taipei Metro network's lack of redundancy and limited spare capacity, especially near overcrowded network segments. Some passengers going through such segments are likely to be re-routed to paths with much longer travel times, hence the increase to average travel time.

4.4.3 Solution Comparison

To evaluate the effectiveness and efficiency of our approach, we compare the result with well-known transit assignment models AON and SUE. Additionally, the result of prominent cooperative multi-agent pathfinding solver (Windowed Hierarchical Cooperative A*) WHCA* (Silver, 2005) is shown to compare the optimality of our solution.

Table 4: Penalty comparison between different algorithms.

Model	Re-route penalty	Wait penalty	Transfer penalty	Total penalty
AON	1186.57	5.74	7.27	1199.58
SUE	1175.34	10.13	7.55	1193.02
WHCA*	1069.76	23.04	12.52	1105.32
MARL	**1049.61**	14.54	10.11	**1074.26**

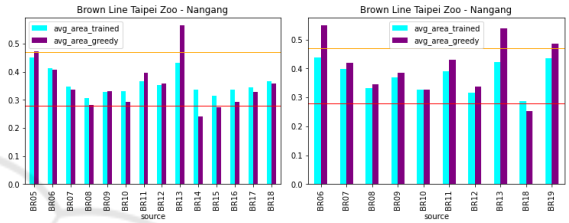
Table 5: Comparison of solution quality between different assignment models.

Model	Slightly packed	Normal	Time delay	GA time delay
SUE	11.05%	22.53%	0.53 m	1.78 m
WHCA*	32.88%	**60.01**%	2.68 m	13.4 m
MARL	**57.79**%	46.37%	1.61 m	8.13 m

Table 4 shows the advantages of our approach over AON, SUE and WHCA*. First, our approach converges to lowest re-route penalty in comparison with the others. Second, congestion is relieved with minimum cost overhead. This is reflected through lower wait and transfer penalty compared to WHCA*. To further demonstrate the ability of our cooperative route recommendation system to reduce congestion, additional evaluation metrics is shown (Table 5). It can be seen that our solution reduced number of passengers experiencing highest level of congestion by 57.79%. Even though WHCA* converted more slightly packed passengers to normal level of congestion (60.01%), it failed to re-route large number of passengers who travel through packed routes. Furthermore, time delay incurred by guided agents (GA) following our guidance is 8.13 minutes on average, which is lower than WHCA* (13.4 minutes).

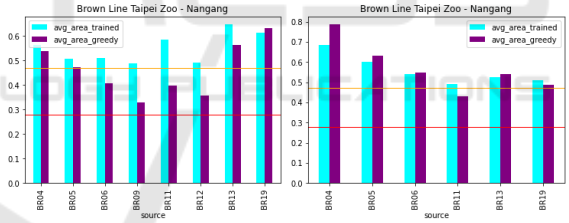
4.5 Discussion

From the analysis in the previous sections, the proposed approach in this paper can efficiently distribute metro passengers from congested routes to under utilized but slower routes by using multi-agent reinforcement learning technique and processed AFC data.



(a) 08:00-08:30 (b) 08:30-09:00

Figure 6: Average passenger area of slightly packed trains along Brown line - Taipei Zoo - Nangang.



(a) 08:00-08:30 (b) 08:30-09:00

Figure 7: Average passenger area of normal trains along Brown line - Taipei Zoo - Nangang.

Figure 6a shows that the learned policy tries to increase the level of comfort of trains at overly crowded stations BR08, BR10, BR14 and BR15. In order to do that, it makes the distribution of passengers at each station more evenly distributed by delaying some passengers' departure time. The effect of enforcing this policy can be seen in Figure 6b where the average area in almost all of slightly packed trains becomes smaller, in other words increasing the level of crowdedness in almost all slightly packed trains. Moreover, we can see from Figure 7a and 7b that there are no trains at stations BR07, BR08, and BR10 that belong to normal level of crowdedness. All trains passing through these stations are either crowded or slightly crowded. These stations are the main bot-

tleneck along Brown line and hence more advanced strategy should be enforced at these stations to improve social distancing.

5 CONCLUSIONS

In this paper, we addressed the problem of multi-class transit assignment in a congested network using multi-agent cooperative route guidance system trained with reinforcement learning method. We decompose the problem of assigning passengers to routes as a decision making problem at each stop and formulate it as Markov games. We then propose TransMARL, a multi-agent reinforcement learning method based on Proximal Policy Optimization (PPO) algorithm with several adaptations, including parameter sharing and a curriculum learning component that speeds up the training process. Empirical results show that in terms of solution quality, TransMARL can successfully reduce overcrowding in critical routes by 57.79% with only 8 minutes time delay.

There are some improvements that could be incorporated to multi-agent actor critic model in order to increase the overall performance. This work has been mainly focused on the use of centralized learning decentralized execution and parameter sharing techniques, leaving the study of other approaches to induce cooperative behavior outside the scope of this paper. The following ideas could be tested:

1. The importance of inter-agent communication to solve tasks that require synchronization has been long studied. To achieve strong coordination, a shared communication memory is used. Agents then learn information sharing and extraction protocol through the shared memory (Pesce and Montana, 2020).
2. In a partially observable environment, each agent has no knowledge of other agents' goal/destination. Consequently, the agents must infer other agents' hidden goal and policy in order to solve the task. There are several ways to do this: learn a separate representation of other agents' policy, use agent's own policy to predict other agents' action, and learn other agents' policies directly from other agents' raw observation.
3. Even though the above-mentioned ideas could potentially increase the overall performance significantly, it remains a challenge to make those approaches scalable to large number of agents. One possible solution is to estimate the degree of influence of other agents' policy on current agent's reward and only agents with high degree of influence are taken into consideration (Jaques et al., 2019).

The path allocation model developed in this work mainly focuses on two user classes: guided and unguided agents. This is based on the assumption of homogeneous users. However, each passenger usually has different route preferences and thus has different utility cost function. For instance, different passengers with same source and destination may choose different routes based on their preferences (time-efficient or congestion-free). An important direction of future work is to develop a personalized route recommendation that takes individual route preferences into account.

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