# Deep reinforcement learning based AGVs real-time scheduling with mixed rule for flexible shop floor in industry 4.0

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## Deep reinforcement learning based AGVs real-time scheduling with mixed rule for flexible shop floor in industry 4.0

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ABSTRACT

Driven by the recent advances in industry 4.0 and industrial artificial intelligence, Automated Guided Vehicles (AGVs) has been widely used in flexible shop floor for material handling. However, great challenges aroused by the high dynamics, complexity, and uncertainty of the shop floor environment still exists on AGVs real-time scheduling. To address these challenges, an adaptive deep reinforcement learning (DRL) based AGVs real-time scheduling approach with mixed rule is proposed to the flexible shop floor to minimize the makespan and delay ratio. Firstly, the problem of AGVs real-time scheduling is formulated as a Markov Decision Process (MDP) in which state representation, action representation, reward function, and optimal mixed rule policy, are described in detail. Then a novel deep q-network (DQN) method is further developed to achieve the optimal mixed rule policy with which the suitable dispatching rules and AGVs can be selected to execute the scheduling towards various states. Finally, the case study based on a real-world flexible shop floor is illustrated and the results validate the feasibility and effectiveness of the proposed approach.

[HTML] Deep **reinforcement learning** based **AGVs** real-time **scheduling** with mixed rule for flexible shop floor in industry 4.0

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… still exists on **AGVs** real-time **scheduling**. To address these challenges, an adaptive deep **reinforcement learning** (DRL) based **AGVs** real-time **scheduling** approach with mixed rule is …

## Background

- **Automated Guided Vehicle(AGV)**
  - **(Role)** Transporting products or materials within a manufacturing facility or warehouse
  - **(Operational)** Dispatching, Scheduling, Routing, Roadmap generation
  - **(Issues)** Multiple / Heterogeneous AGVs, Collision, Bottleneck, Charging,
    Centralized / Decentralized control of AGVs

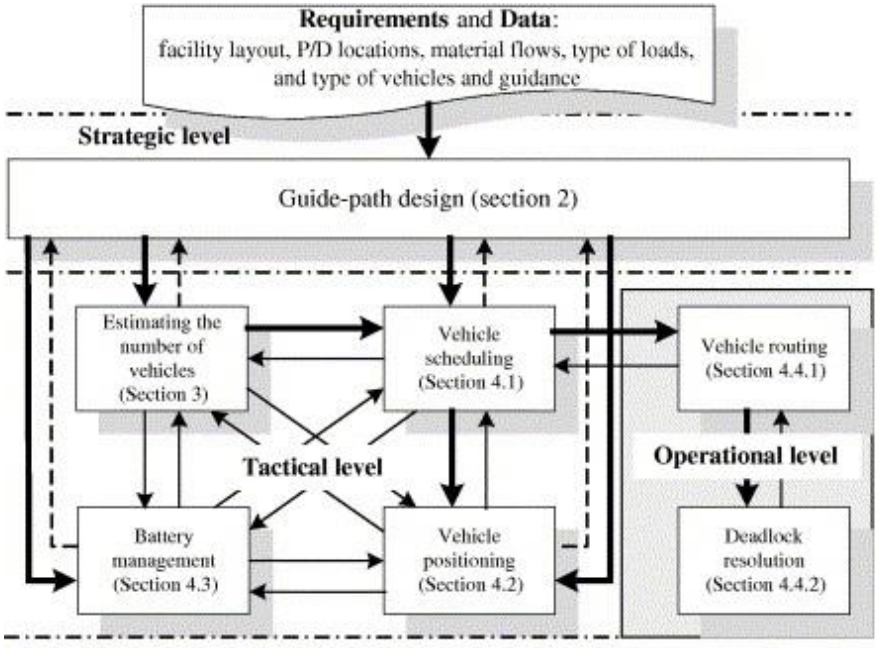



Fig.

"A review of desing and control of automated guided vehicle systems." Le-Anh Tuan. 2006.

# Problem definition

## ▪ AGV scheduling problem

- We want to optimize the allocation and sequencing of tasks for AGVs.

→ Determining <u>which task should be done</u> and <u>which AGV should perform the task</u>

- **Key objectives**
  - Minimizing travel time
  - Minimizing waiting time
  - Balancing workload
  - Optimizing resource utilization
  - Meeting deadlines

- **Challenges**
  - Multiple AGVs
  - Layout of the facility
  - Task priorities

# Related works

| Year | Paper |
|---|---|
| 2020 | A Deep Reinforcement Learning Based Approach for AGVs Path Planning |
| 2021 | Decentralized Multi-AGV Task Allocation based on Multi-Agent Reinforcement Learning with Information Potential Field Rewards |
| 2022 | Real-time Automated Guided vehicles scheduling with Markov Decision Process and Double Q-Learning algorithm |
| 2023 | A Multi-AGV Routing Planning Method Based on Deep Reinforcement Learning and Recurrent Neural Network |
| 2023 | Anti-conflict AGV path planning in automated container terminals based on multi-agent reinforcement learning |
| 2024 | Interaction between a Human and an AGV System in a Shared Workspace—A Literature Review Identifying Research Areas |

- **Previous works**
  - Rule-based or heuristic approaches to the problem.
  - There were not much novel studies within the RL approach.

- **Contribution**
  - Solving the real-time scheduling problem with the simulation based RL
  - Well organized paper

# Problem formulation

## ▪ MDP formulation

- State

$$S_t = (\underbrace{N_t, T_{art}, D_{adt},}_{\text{Task info}} \underbrace{A_{st}, A_{vt}}_{\text{AGV info}})$$

  - $N_t$ : The number of the current tasks
  - $T_{art}$ : The average remaining time of the current tasks (average urgency)
  - $D_{adt}$ : The average travel distance of the current tasks (average workload)
  - $A_{st}$ : The availability status of AGVs (binary)
  - $A_{vt}$ : The normal driving speed of the AGVs (3 types of AGV)

- Action

$$a_t = (\underbrace{R_{u_t},}_{\text{Selecting dispatching rule}} \underbrace{AGV_t}_{\text{Selecting an AGV}})$$

Selecting dispatching rule → 5 rules →

- FCFS(First Come First Serve)
- STD(Shortest Travel Distance)
- EDD(Earliest Due Date)
- LWT(Longest Waiting Time)
- NVF(Nearest Vehicle First)

# Problem formulation

## ▪ MDP formulation(cont'd)

- Reward

  - Current reward : $R_t = \underbrace{\mu_1(c_{ad} - C_{ikd})}_{\text{Delay cost}} + \underbrace{\mu_2(c_{aT} - C_{ikT})}_{\text{Time cost}}$

    - $c_{ad}$ : the average delayed cost for a task
    - $C_{ikd}$ : the delay cost after AGV i executing the task k
    - $c_{aT}$ : the average time cost for a task
    - $C_{ikT}$ : the time cost after AGV i executing the task k

  - Final reward : $R_f = \underbrace{\mu_1(C_{ad} - C_d)}_{\text{Delay cost}} + \underbrace{\mu_2(c_{aT} - C_T)}_{\text{Time cost}}$

    - $C_{ad}$ : the average delayed cost for the whole scheduling
    - $C_d$ : the total delay cost of the whole scheduling
    - $C_{aT}$ : the average time cost for the whole scheduling
    - $C_T$ : the time cost of the whole scheduling(makespan)

# Example for an episode

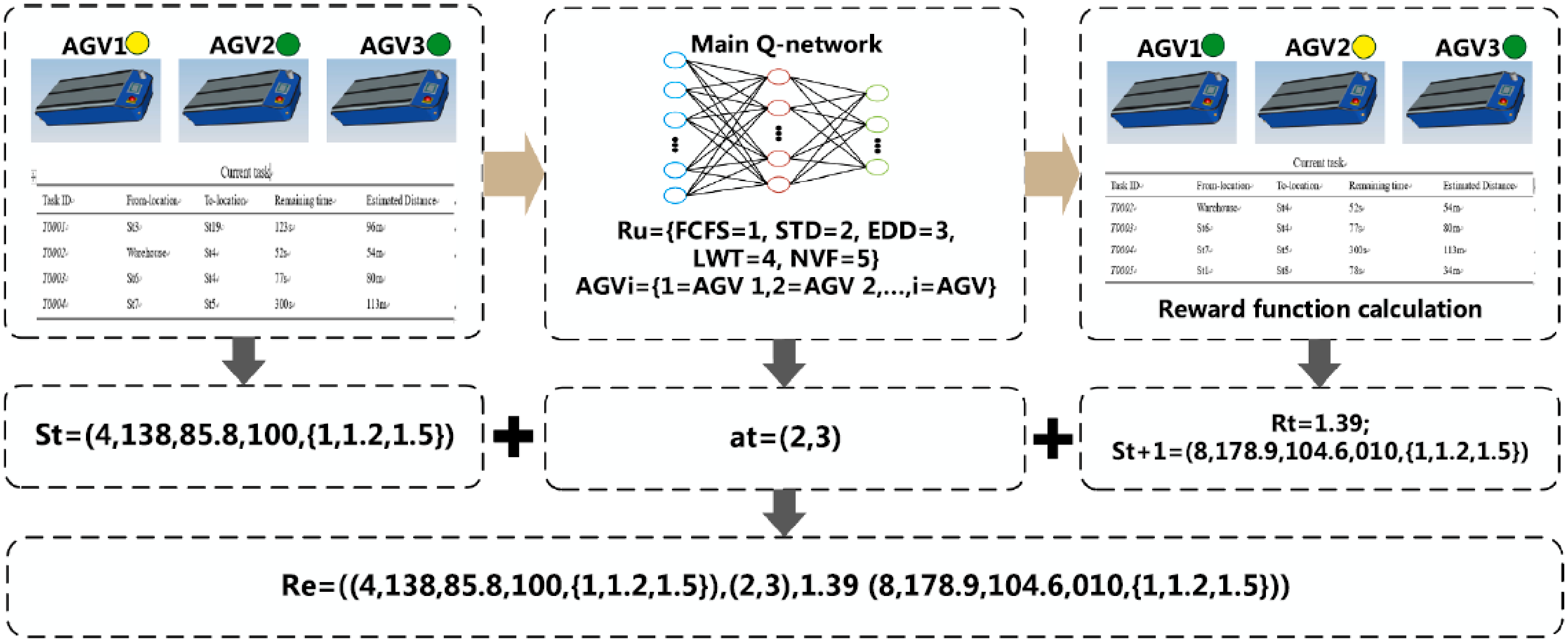



**Fig. 6.** The training process demonstration for an episode.

# Architecture of DRL

- DQN based AGVs scheduling

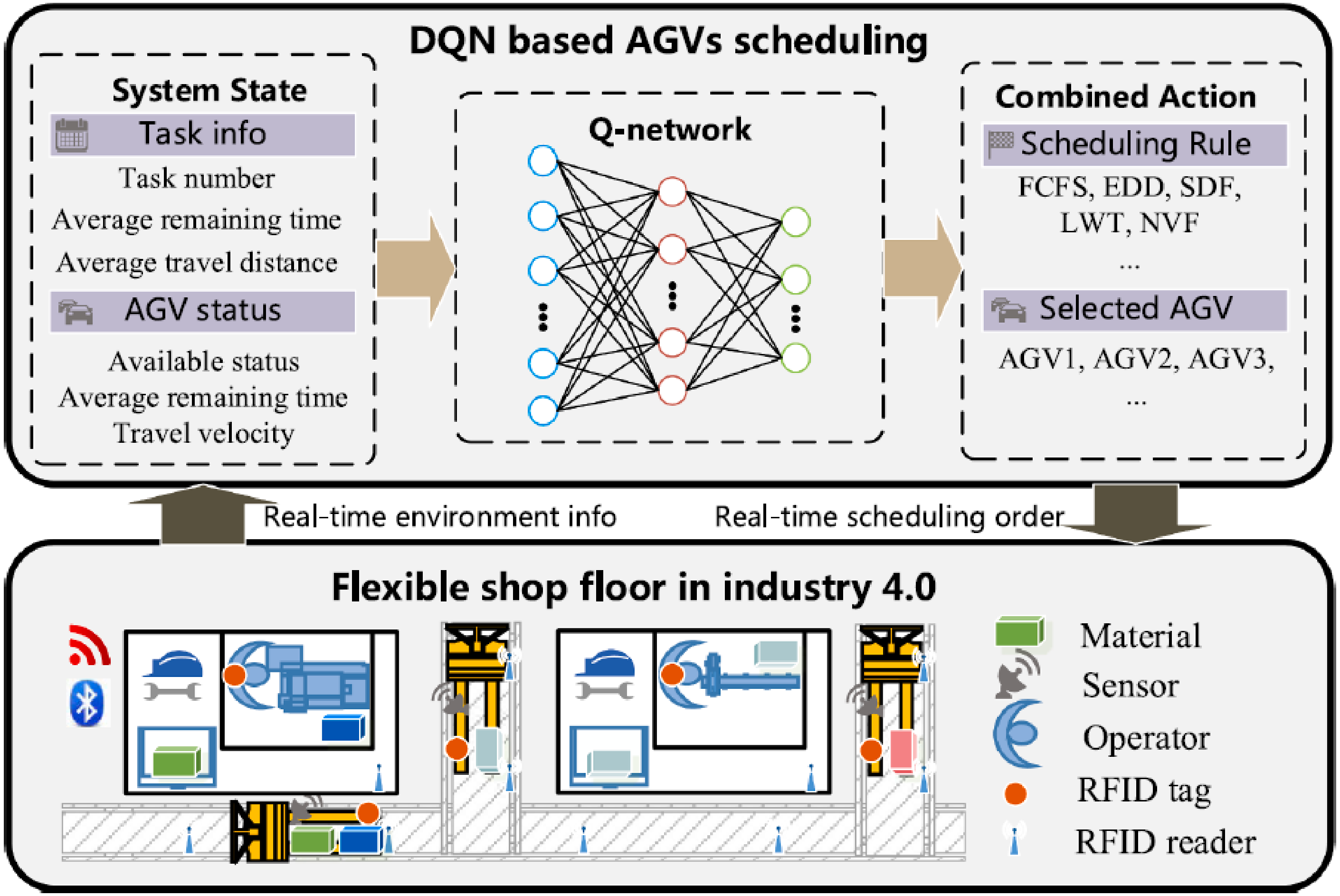



**Fig. 1.** Architecture of AGVs real-time scheduling approach using DRL.

## Training algorithm

- DQN algorithm

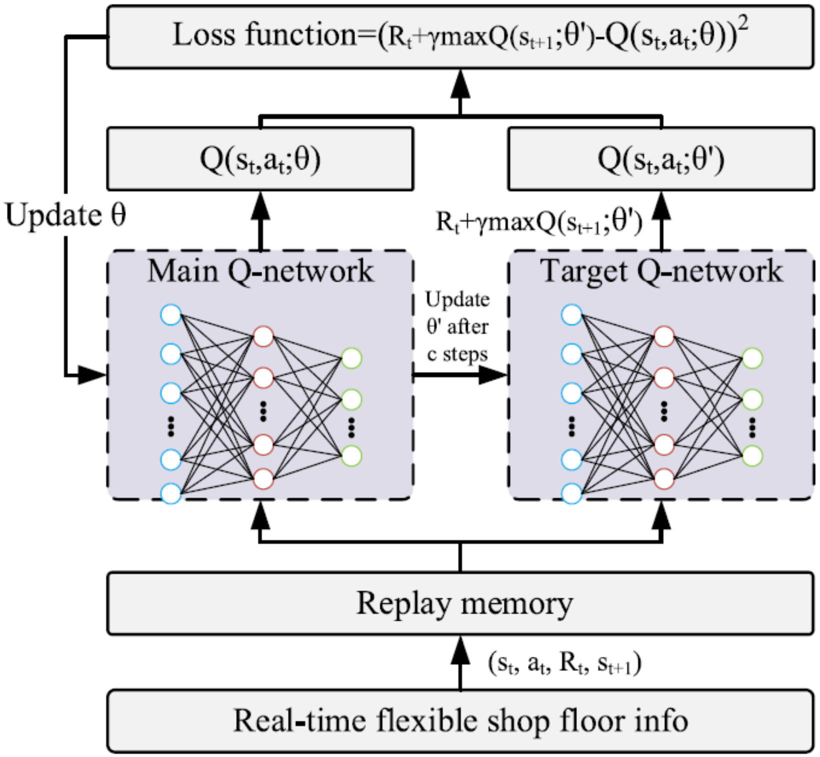



**Fig. 2.** Primary steps of the training algorithm.

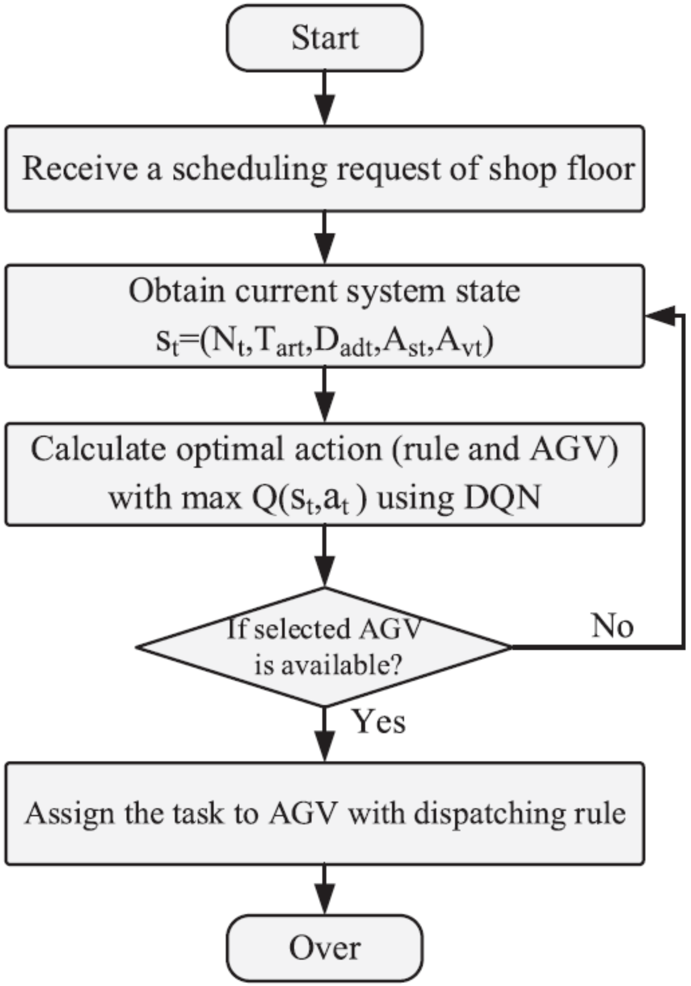
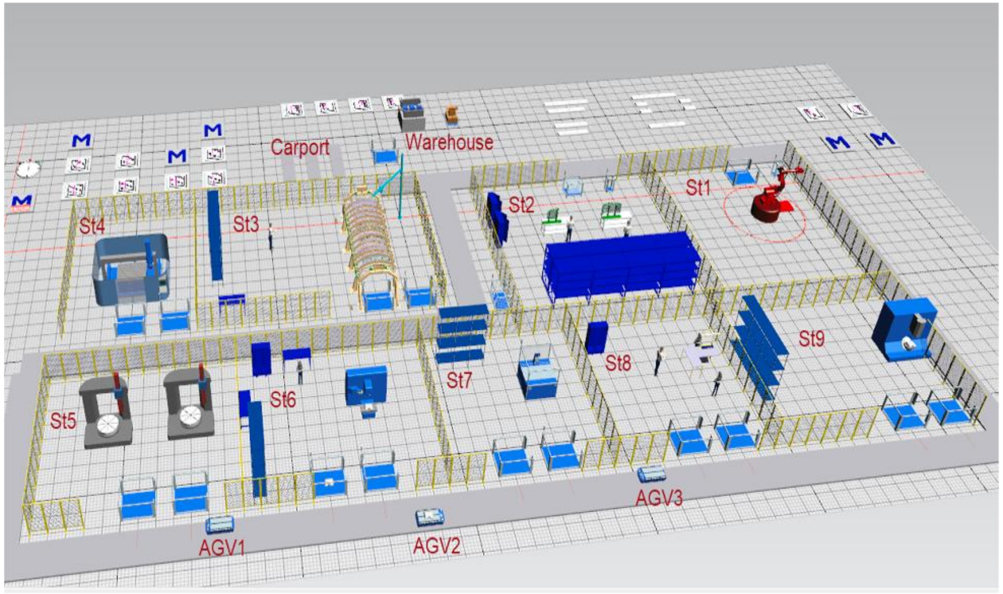



**Fig. 3.** AGVs real-time scheduling with optimal mixed rule policy.

# Experiment settings

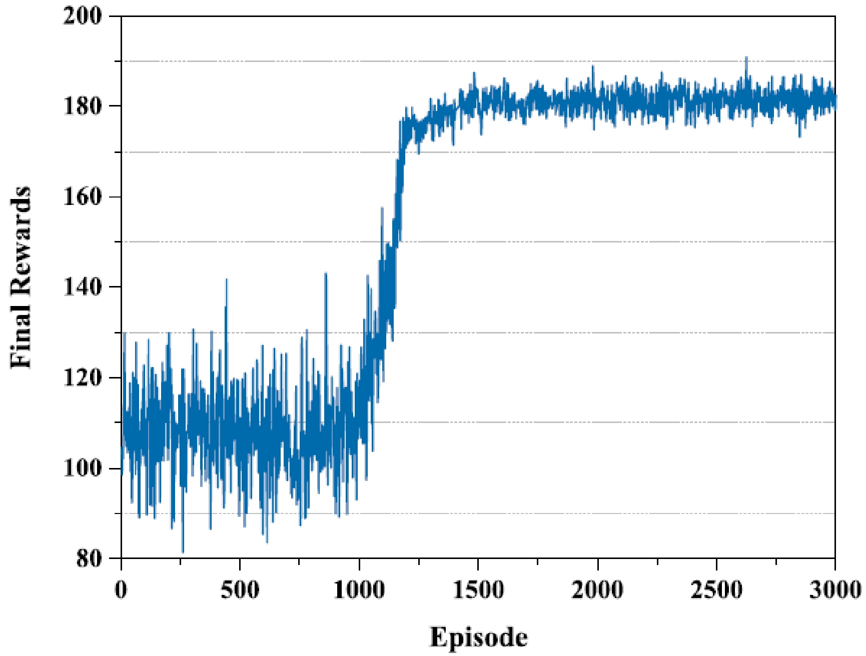
- Simulation case
  - AGVs must come back to carport when a task is done
  - 800 tasks for an episode
  - maximum tasks up to 20
  - 3 different AGVs
  - 2 buffers for loading & unloading
  - Shortest route policy
  - Collision ignored



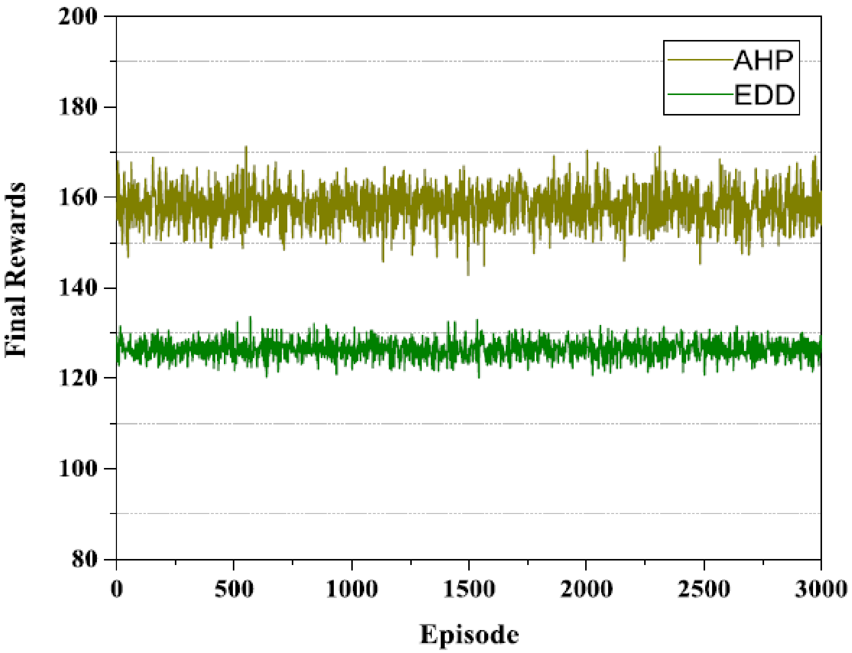

Simulation software
(Siemens Tecnomatix )

# Experiments

- Comparison of the final reward with training
  - The final reward increased rapidly after training 1,000 episodes.
  - DQN achieved the better performance than the rule based models.
  - AHP, EDD showed more stable results without any learning.



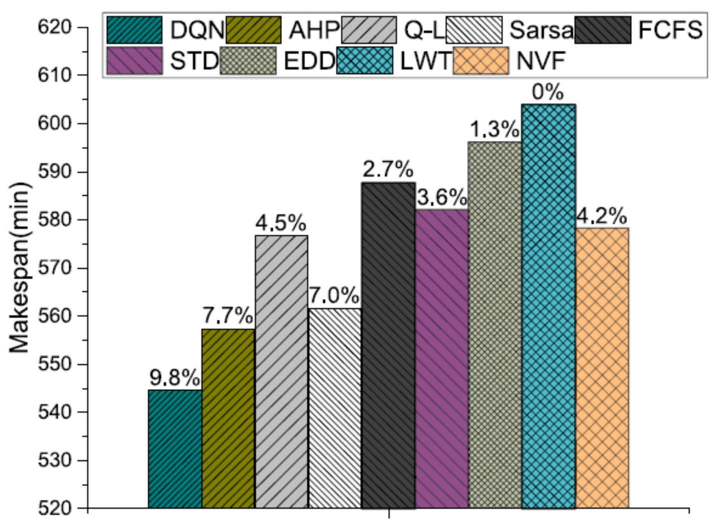

(a) The evolution of DQN



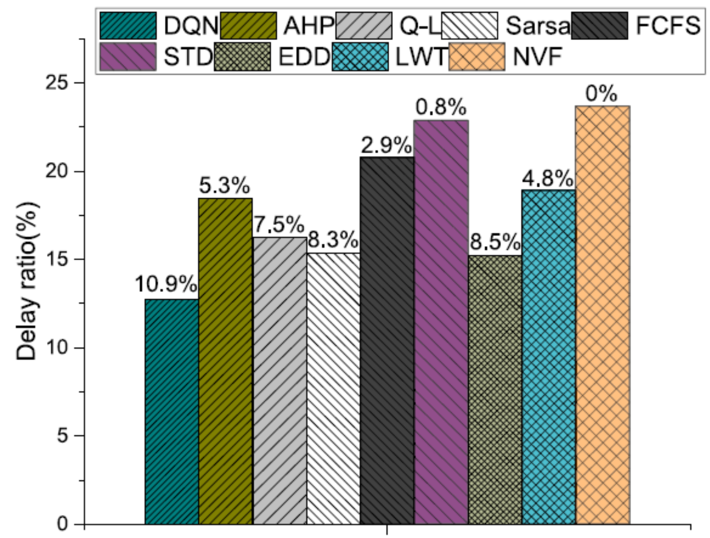

(b) The evolution of AHP and EDD

# Experiments

- Comparison of the various methods
  - They compared the Q-learning, SARSA and rule-based methods.
  - DQN achieved the 9.8% improvement in makespan and 10.9% improvement in delay ratio.



(a) Improvements of makespan



(b) Improvements of delay ratio

# Conclusion

- **Conclusion**

  - They suggested DQN based method for the AGV scheduling problem.
  - Proposed method outperformed the rule-based dispatching methods.
  - Achieved about 10% improvement of makespan and delay ratio.

- **Further research**

  - Need of accurate simulation settings
  - Scalable issues (size of facility, the number of AGVs)
  - Task with various priorities
  - Handling collision & deadlock problem