Virtual Commissioning for an Overhead Hoist Transporter   
in a Semiconductor FAB

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**Abstract**: Presented in the paper.

**Key words:** HILS, OHT, Virtual commissioning, Control software verification

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**1. INTRODUCTION**

Increasing global competition and a shift towards customer-centric markets in most industries poses challenges for manufacturing enterprises. Their production and logistic processes must have a high level of logistic quality, expressed by KPIs such as average throughput time or mean tardiness, to satisfy customers’ demands while incurring low logistic costs to ensure competitive-ness. This requires the careful design of operational planning and control processes. Positioning an enterprise and choosing or developing the most suitable planning and control methods is a difficult and time-consuming process, currently often performed manually in a trial-and-error fashion.

Manufacturing environments are often too complex to consider all important attributes, because the requisite information comes from multiple sources and sensors, and also because much of the underlying logics of the operation might be implicit and challenging to capture intuitively. Thus, extraction of implicit knowledge from given schedules enables smart factories to automate the development of dispatching rules while reflecting various attributes.

✁ Figure 2. Commissioning configurations ✁

Automated Guided Vehicles (AGVs), a kind of mobile robot for material handling, have been regarded as one of the most promising technologies and applied to various shop floors and warehouse logistics for material supply operations owing to high degree of autonomy and flexibility (Vis, 2006; Michalos, Kousi, Makris, & Chryssolouris, 2016; Kousi et al., 2016; Demesure et al., 2018; Wang, Zhang, & Zhong, 2020; Kousi, Koukas, Michalos, & Makris, 2019).

Dispatching rules classified a vehicle-initiated task and a workcenter-initiated task assignment (Tanchoco 1984). Depending on the situation, traditional dispatching rules are used to dispatch AGVs using only single method or multi mixed methods. These rules are First Come First Served (FCFS), Shortest Travel Distance (STD), Earliest Due Date first (EDD), Longest Waiting Time (LWT), Nearest Vehicle First (NVF), Maximum Queue Size (MQS), etc. To solve dispatching problem, some cases adopted reinforcement learning. **Reinforcement learning is a machine learning method that can constantly adjust agent’s behavior through trial and error** (Kaelbling, Littman & Moore, 1996). **[Scheduling problem]** An reinforcement learning based approach for a multiple-load carrier scheduling problem (Chen, Xia, et al. 2015), and they proposed Q() model improve throughput and reduce travel cost. Vehicle-initiated task assignment approach production scheduling problem using Q-learning algorithm (Wang and Usher, 2005). In dynamic job shop scheduling problem approach using reinforcement learning. **The other effective cases**, Dispatching solution based on Q-learning, wherein the functions are approximated with a neural network (NN), can be used to reduce the complexity inherent to centralized learning. Because a Q-learning-based solution is easy to control for a discrete time, coordination with discrete event simulation (DES) has great value (Park, Huh et al. 2019; Gabel and Riedmiller 2008; Gosavi 2009). Wang et al. (2015) proposed dueling networks with two separate estimators for the state value function and state dependent action advantage function. The dueling networks separately learn V(s), which is determined only by the state, and the advantage A(s, a), which is determined according to actions, to derive Q(s, a). This approach has the advantage of being able to divide the information of the Q-function into the portion determined only by the state and that determined according to actions. In contrast to a deep Q-network (DQN), it learns the combined weights that lead to V(s) at every step regardless of the action. Moreover, it requires fewer episodes than a DQN to complete learning, resulting in better performance as the number of action types increases (Wang et al. 2015; van Hasselt, Guez, and Silver 2016; Nair et al. 2015; Gosavi 2009).

**2. PROBLEM FORMULATION**

State, s is the geo-coordinates of the driver and time-of-day (in seconds) when the driver is dispatched for a trip order, i.e. s := (l, t), where l is the GPS coordinates pair (latitude, longitude) and t is time. Note that it could be different from the actual origin of the trip where the passenger stands at. Moreover, s may contain additional contextual features at (l, t), such as statistics of demand, supply, and order fulfillment within the vicinity of (l, t), denoted as f. In this case, s can be extended from (l, t) to (l, t, f). We also differentiate the time for weekday and weekend. For the rest of the paper, we denote the l and t components of a state s by sl and st respectively.

Action, a is the assignment of a particular trip to the driver, which is simply defined by the trip destination and drop-off time. Let the current state s0 := (l0, t0, f0) be the driver’s location, time and the context when the trip is assigned, and the next-state s1 := (l1, t1, s1) is the drop-off location, time and context. Then, the action is a = (l1, t1). The space of all eligible actions is denoted by A.

Reward, r is the total fee collected for the trip and is a function of s and a.

An episode is one complete day, from 0:00am to 23:59pm. Hence, a terminal state is a state with t component corresponding to 23:59pm. We set s1 in all those transitions where the trip crosses midnight to be terminal state.

State-action value function, Q(s, a) is expected cumulative reward that the driver will gain till the end of an episode if he/she starts at state s and takes an action a. Mathematically, Q(s, a) := E T t=0 γt R(St, At)|S0 = s, A0 = a , where S, A, and R are stochastic variable version of s, a, and r respectively; T is the number of transition steps till the terminal state, and γ is the discount factor for the future rewards. We discretize the time space into steps of 10 minutes and γ is multiple powers of the time steps that an order strides across.

Policy, π(a|s) is a function that maps a state s to a distribution over the action space (stochastic policy) or a particular action (deterministic policy). The greedy policy with respect to a learned Q(s, a) is given by π(s) := arg maxa Q(s, a). State value function, V (s): expected cumulative reward that the driver will gain till the end of an episode if he/she starts at state s and follows a policy π. Assuming that a greedy policy w.r.t. the Q function is used, the state value V (s) := Q(s, π(s)) = maxa∈A Q(s, a).

In this paper, t-step simulation environment clip image as input approach real-time AGV dispatching problem using multi-agent method of reinforcement learning conclude CNN and GNN.

2.1. State representation

**State raw observation full state**

State at t-step is separable term represented multi-matrix form meaning 3-channel image (127 by 127). Environment clip image is program screen of human level. And Feature Image show AGVs, Current Job, and Simulation attributes as color image. conclude Red channel image is represented job information. Green Channel image is represented each link’s driving constraints such as direction, velocity, and rotation. Blue channel image is represented sequence information about time-horizon AGV routing left.

Finally, mask make block unnecessary region. It’s predefined static matrix.

2.2. Reward representation

Many researcher are trying well-made reward function, several good reward function design cases, ‘Deep Mimic’ and ‘GAIL(**dd**)’ are used exponential form into kinematic models. If demonstrate agent get valuable experience by non-linear functions. Also, we refer multi attributes rule, selected throughput, waiting time, and mileages. We make non-negative reward function.

2.3. Action representation

Action represents the dispatching rule of the AGV’s system and is defined by a encoding value Dispatching rules in action are First Come First Served (FCFS), Shortest Travel Distance (STD), Earliest Due Date first (EDD), Longest Waiting Time (LWT), Nearest Vehicle First (NVF), and Maximum Queue Size (MQS).

The state represents separable matrix form at time t . Each observation merged to state in AGV. Critic network adjust weights from value function. And Actor network give action strategy to Environment. Mix-up method is one of feature extract methods. And select RasNet-50 fine-tune method transfer learning

2.3. Policy representation

Policy is a approximator estimated future action by decision boundary in reinforcement learning. Generally, policies are adjusted by value function.

Value function 수식

GraphMix

Q-learning

✁ Figure 3. OHT design & production procedures ✁

**3. VIRTUAL OHT MODEL CONSTRUCTION**

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**4. DISCUSSION AND CONCLUSIONS**

In a large FAB,

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