Evaluating Joint Delivery Systems using Multi-Agent Simulation Models Adaptive Dynamic Programming

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This paper present multi-agents systems (MAS) combine with a novel adaptive dynamic programming (ADP) for evaluating joint delivery systems with Urban Consolidation Centres (UCC). ADP performs particularly well in dynamic multi-agent system. We investigate this hypothesis by comparing ADP with one of the most popular Reinforcement Learning algorithms namely Q-learning. ADP gives lower delivery cost as compared to Q-learning for the random demand experiment.

Key Words: *Adaptive dynamic programming, multi-agent system, city logistics, urban consolidation centre*

1. INTRODUCTION

Urban freight transport plays an important role in both developed and developing countries in the world due to the population density in urban areas as well as social, economic, and environmental problems associating to the urban freight transport. Recently urban freight transport faces a difficult problem related with unpredictable travel time due to traffic congestion in the urban area. This means that the delivery environment in the urban area is unpredictable, which effects directly to both the operational cost and the optimal action selection. In contrast, freight carriers are expected to provide higher services and lower costs.

City logistics is defined as the process for totally optimizing the logistics and transport activities by private companies with support of advanced information systems in urban areas considering the traffic environment, the traffic congestion, the traffic safety, and the energy savings within the framework of a market economy[1)]. In order to deal with those purposes, numerous city logistics initiatives have been proposed and implemented in several cities, including Urban Consolidation Centres (UCC), parking restriction, and load factor controls. Moreover, new model and evaluation methods are required to conduct in depth-investigations before city logistics initiatives can be effectively deployed[2)].

The core idea of this research is evaluating city logistics measures using multi-agent models with adaptive dynamic programming (ADP). As the preliminary research, this research developed and tested ADP in a simple case of agent-based system in order to understand the behavior of ADP within a dynamic environment.

As city logistics aims at total optimization of costs and benefits, it is appropriate to adopt Multi-Agents Systems (MAS) for evaluating city logistics measures, which consider the objectives and behavior of several city logistics stakeholders. The main stakeholders in city logistics are freight carriers, shippers, customers, and administrator. All of these key stakeholder in urban freight transport have their own specific objectives and tend to behave in a different manner to any urban freight policy. City logistics models need to incorporate these factors[1)].

This research combines MAS and ADP in the evaluation method of city logistics measures to accommodates an agent's perception that optimizes its behavior with its environment and learning from the feedback received. The evaluation of the long-term performance of utility is optimized by learning a value function that predicts the future rewards over time. For that purposes we developed a MAS-ADP model for freight carrier in this preliminary research, and also we tested the model in a simulation of the city logistics policy.

2. LITERATURE REVIEW

The combination between MAS model with reinforced learning (RL) algorithms has been used for evaluating the behavior of stakeholders who are affected by the implementation of a city logistics policy. For example; 1) MAS with Q-learning algorithm has been used to evaluate the dynamic usage of UCC[4, 31], road pricing[5], e-Commerce[6], toll pricing[7], truck ban[8], time windows restrictions[9], load factor control[10], and Joint Delivery System (JDS) with parking restrictions[11]; and 2) MAS with Monte Carlo Method was used by Taniguchi, Yamada, and Okamoto[12] in the dynamic vehicle routing and scheduling systems.

ADP is a novel algorithms in RL that has recently become a hot topic in the fields of both optimal control and simulation. Some research experiences have conclude that ADP is able to deal with uncertainty[13, 14], stochastic environment[15, 16], and non-linearity[17]. ADP faces these challenges by constructing optimal control methods that enable to adapt under uncertainty environment and do a simulation of value functions to decide the best actions. Zhang, et al.,[17] has reviwed some research on the applications of ADP at the confluence of control problem[18, 19], intelligence traffic systems[20, 21, 22, 23, 3], robotics[24], navigation system[25], communication systems[26], and aircraft controller[27].

However, none of those previous research has used the ADP within MAS in the area of city logistics. Hardin[28], conclude that learning and adaptation make the system more robust to imperfect knowledge of the environment. While, stability results of a model is important in decision making due to the urgency of proposing efficient action selection. Therefore, this research aims at evaluation of city logistics measures using multi-agent models with ADP in order to provide more adaptative and stable results. Hopefully, the readers would get a preliminary understanding about the behavior of ADP within MAS through this paper, so as ADP could be applied to both complex simulation and optimization problems in city logistics.

3. MODELS

(1) Markov Decision Problems

The famed approach to agent-based systems is to define them as Markov Decision Processes (MDP), which consists of a state (S), action (A), transition (T), and reward (R). Here, S is a set of total states within the systems; A is a set of total actions those can possibly be taken by an agent; and T basically is a function of state transition that the agent did to get the optimal value. The agent's policy π is a mapping of the actions that an agent will take in any given state system. Thus, the objective of the agent is determining a policy π:S→A which results in the optimum utility. Utility or value function is the performance index that should be optimized based on the objective function. The state value function (V) is agent's long-term utility for any given state. Therefore, utility not only refers to an immediate reward that can be received after doing action but also to the sum of future rewards that can be expected either when following the agent's policy or when choosing the action that impacts to the highest immediate reward.

(2) Adaptive Dynamic Programming (ADP) within MAS

ADP learns the model of the environment and then applying a DP algorithm to solve the MDP and updates its state action utility value using the expected transfer value function and expected reward function as follows;

$$T(s_t,a_t) \leftarrow T(s_t,a_t) + \alpha(t(s_t,a_t) - T(s_t,a_t)) \qquad (1)$$

$$R(s_t,a_t) \leftarrow R(s_t,a_t) + \alpha(r(s_t,a_t) - R(s_t,a_t)) \qquad (2)$$

Where,

$T(s_t,a_t)$: expected transfer in state t when action a is taken from state s_t

$t(s_t,a_t)$: observed transfer in state t when action a is taken from state s_t

α : learning rate of freight carrier ($0 < \alpha < 1$)

$R(s_t,a_t)$: expected reward when action a is taken from state s_t

$r(s_t,a_t)$: observed reward when action a is taken from state s_t

The state action utility value of MAS-ADP is dynamically calculated using the equation 3 below;

$$V(s_t,a_t) \leftarrow R(s_t,a_t) + \gamma \sum_{s' \in S} T\left(s_{t+1} \middle| s_t,a_t\right) V(s_{t+1},a_{t+1}) \qquad (3)$$

Where,

$V(s_t,a_t)$: expected utility value (delivery costs) in state s_t due to action taken in state s_t

$V(s_{t+1},a_{t+1})$: expected utility value (delivery costs) in the next state s_{t+1} of all actions

γ : discount rate of freight carrier ($0 < \gamma < 1$)

$T(s_{t+1}|s_t, a_t)$: expected transfer to state s_{t+1} when action a is taken from state t

The decision variable in this research is $r(s_t, a_t)$ which the observed reward for choosing two actions below;

$$r(s_t, a_t)\begin{cases}(uccfee*No.parcel)\text{, if } a_t \text{ is joint UCC in } s_t\\(VRPSSTW\cos t + parking\cos t)\text{, otherwise}\end{cases}$$

The observed reward as ($UCCfee * No.parcel$) is basically the total delivery costs paid by freight carrier for joining delivery with UCC. The UCC fee is charged by UCC operator for delivery service per parcel. Then, freight carrier will pay the costs of delivery service based on the total number of delivered parcels (demand) multiplied with UCC fee. Otherwise, freight carrier will receive reward as ($VRPSSTW\cos t + parking\cos t$), if they decide to deliver goods directly to their customer. VRPSSTW (Vehicle Routing Problem with Semi-Soft Time Windows) cost is a total costs to do delivery and pickup goods activities of freight carrier. VRPSSTW is the extension of Vehicle Routing Problem with Time Windows (VRPTW) that has been modelled by Qureshi, et al. [30]. In addition, parking cost might be added in delivery costs for direct delivery action.

(2) Q-learning within MAS

To evaluate our ADP models, we firstly compare the simulation results of ADP with freight carrier's Q-learning model that has been modelled by Wangapisit, et al.,[11] as described in following equation 4. Q-learning learns an actions value function of Q instead of a state value function and updates its state action utility value using the model as follows;

$$Q(s_t, a_t) \leftarrow (1-\alpha)Q(s_t, a_t) + \alpha\left[r_{s_t, a_t} + \gamma \max_{a' \in A} Q(s_{t+1}, a_{t+1})\right] \quad (4)$$

Where,

$Q(s_t, a_t)$: Q-value in state t due to action taken in state s_t

$Q(s_{t+1}, a_{t+1})$: Q-value in the next state s_{t+1} of all actions

γ : Discount rate for freight carrier $(0 < \gamma < 1)$

α : Learning rate for freight carrier $(0 < \alpha < 1)$

r_{s_t, a_t} : Transportation cost and unexpected ad ditional cost such as parking cost at the shopping street.

(3) Vehicle Routing Problem with Soft-time Windows (VRPSSTW)

As the preliminary research, this research developed and simulated ADP models in a simple case of agent-based system which assumed that only freight carrier will learn the UCC policy. The utility function (performance index) of freight carrier is minimizing the total transport costs. Qureshi, et al.,[30], has been proposed the basic model of vehicle routing and scheduling problem with soft time windows (VRPSTW) in the study of the delivery and pickup goods activities of freight carrier as the following explanation.

A directed graph $G = (V, A)$ is represented the VRPSSTW. The axis set V consist the depot axis 0 and set of customers $C = \{1,2, \ldots, n\}$. The arc set A includes of all feasible arcs $(i, j), i, j \in V$. Variable cost c_{ij} and time t_{ij} are linked with each arc $(i, j) \in A$. A set of vehicles (symbolized with K) with capacity (q) are located at the depot to service customer's demands. Demand (d_i) with $d_0 = 0$ is related with axis V. A time window $[a_i, b_i]$ representing the earliest and the latest service time, while b'_i is the extending of latest service time (**Fig. 1**) and c_l is the unit late arrival penalty cost. However, based on a routing decision, the modified arc costs c'_{ijk} depend on the service time (s_{jk}) at customer j by a vehicle k. These costs are calculated as per equation 5. The maximum limit of b'_i is formulated as equation 6.

$$c'_{ijk} = \begin{cases} c_{ij}\text{, if } a_j \le s_{jk} \le b'_j \\ c_{ij} + c_l(s_{jk} - b_j)\text{, if } a_j \le s_{jk} \le b'_j \end{cases} \quad (5)$$

$$b'_i = min\left[b_0 - t_{i0}, b_i + \frac{(c_{0i}, c_{i0})}{c_l}\right] \quad (6)$$

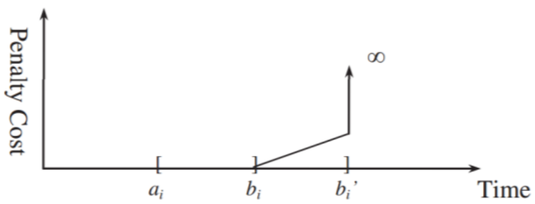

Fig. 1 Penalty cost function for the VRPSSTW

The notation s_{jk} is the start time of service time at an axis $j \in C$ by a vehicle $k \in K$. Thus, Qureshi, et al.,[30] has formulated the mathematical model of VRPSSTW as following;

$$Min \sum_{k \in K} \sum_{(i,j) \in A} c'_{ij} x_{ijk} \quad (7)$$

Subject to;

$$\sum_{k\in K}\sum_{j\in V} x_{ijk} = 1 \qquad \forall i \in C \qquad (8)$$

$$\sum_{i\in C} d_i \sum_{j\in V} x_{ijk} \le q \qquad \forall k \in K \qquad (9)$$

$$\sum_{j\in V} x_{0jk} = 1 \qquad \forall k \in K \qquad (10)$$

$$\sum_{i\in V} x_{ihk} - \sum_{j\in V} x_{hjk} = 0 \qquad \forall h \in C,\ \forall k \in K \qquad (11)$$

$$\sum_{i\in V} x_{i0k} = 1 \qquad \forall k \in K \qquad (12)$$

$$s_{ik} + t_{ij} - s_{jk} \le (1 - x_{ijk})M \qquad \forall (i,j) \in A,\ \forall k \in K \qquad (13)$$

$$a_i \le s_{ik} \le b'_i \qquad \forall i \in V,\ \forall k \in K \qquad (14)$$

$$x_{ijk} \in \{0,1\} \qquad \forall (i,j) \in A,\ \forall k \in K \qquad (15)$$

Decision variables in the formula above is x_{ijk} which represents whether the arc (i,j) is used ($x_{ijk} = 1$) or not $x_{ijk} = 0$. The objective function minimizes the delivery cost (equation 7) and it is subjected to some constraints (equation 8 to 15) which ensure that all routes must start and end at the central depot, respecting the time windows and vehicle capacity. The VRPSSTW model will be used as the utility function of freight carrier in this research.

4. CASE STUDY

We applied MAS-ADP model to evaluate the joint delivery with UCC. The simulations were conducted on a square topology of hypothetical network for testing ADP model within MAS, as illustrated in **Fig. 2** below;

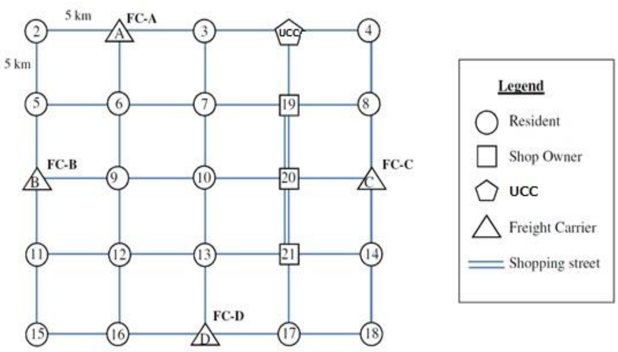

Fig. 2 Test road network

Four carriers (A,B,C,D) are involved in this network. UCC or UDC is a given city logistics policy by the government to this hypothetical city. The MAS-ADP models are iterated for 360 days (1 year) using some assumptions as listed in **Table 1**;

Table 1 Simulation assumptions

VRPSSTW model assumptions
Service time for delivery is from 8 AM to 8 PM
Service time window is 60 minutes (1 hour)
Only one type of truck is available with the capacity designated for 200 parcels
Only one type of goods are served
Demand is distributed randomly for each carrier **(Fig.3)**
Vehicular costs are fixed
Parking cost is 300 Yen for 30 minutes
Penalty charge for early delivery is 1 Yen/ minute
Penalty charge for late delivery is 5 Yen/ minute
Total delivery cost include transportation cost, parking cost, and penalty cost.
MAS-ADP model assumptions
The evaluation period of each carrier is called episode (in total 12 episode within a year)
UCC usage charge is fixed to 150 Yen per parcel
There are two delivery techniques that agents can possibly choose; 1) Joint delivery with UCC and, 2) Direct delivery to the customers

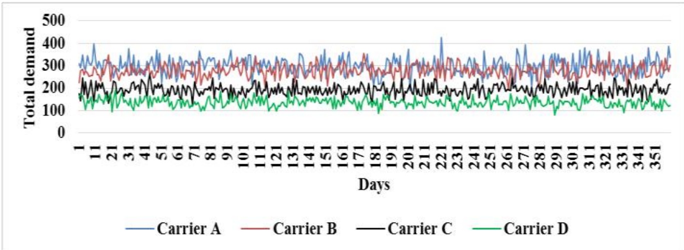

Fig.3 Random distributed demand for each carrier.

The simulation processes are divided into two scenarios;

1. Scenario 1: Normal traffic
   All freight carriers make a decision whether to participate with UCC or not by learning based on the total delivery costs in normal or expected traffic condition.
2. Scenario 2: Traffic congestion
   All freight carriers make a decision whether to participate with UCC or not by learning based on the total delivery costs in the traffic congestion which results in unexpected travel time. We intentionally increased the VRPSSTW costs due to a severe level of traffic congestion that is assumed to happen on roads.

The VRPSSTW costs in Scenario 1 and 2 are given in **Fig. 4** and **5**.

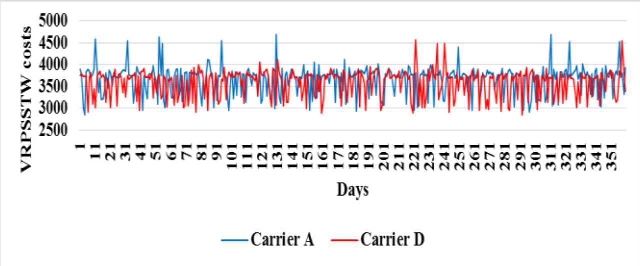

Fig. 4 Typical VRPSSTW costs in normal traffic condition

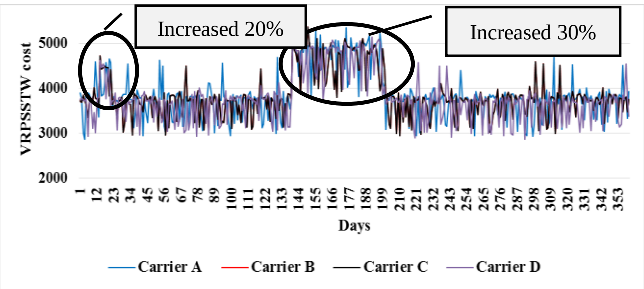

Fig. 5 VRPSSTW costs in traffic congestion

5. RESULTS AND DISCUSSIONS

All the simulations are done in MATLAB with the different settings of learning rate and discount factor for ADP and Q-learning models based on the result of a sensitivity analysis that has been done prior to the case study. The learning rate and discount factor for ADP have been used as 0.2 and 0.6, respectively, whereas learning rate and discount factor for Q-learning have been set as 0.2 and 0.8, respectively. The simulations were conducted in a multi-agents settings, where all freight carriers are attempting to learn at the same time under a dynamic environment. The first set of simulations was conducted in a normal traffic condition (scenario 1). These are used as the base case simulations to show how well the ADP performs within the known/static environment as far as the travel time is concerned. The second simulation places the freight carriers in a traffic congestion situation (scenario 2). These simulations are used to study the behavior of ADP in suddenly changing/ dynamic or unknown environment.

On average, ADP gives more than 3.5% reduction in delivery cost as compared to Q-learning for the random demand experiment. Specifically, the results of delivery costs of carriers A and B are about 3.7% lower than the corresponding costs in Q-learning results (figure 8). In case of carriers C and D, ADP provides 3.6% lower delivery costs (figure 8). It must be noted that low delivery costs is better due to the objective function of freight carrier that aims at minimization of the total delivery costs.

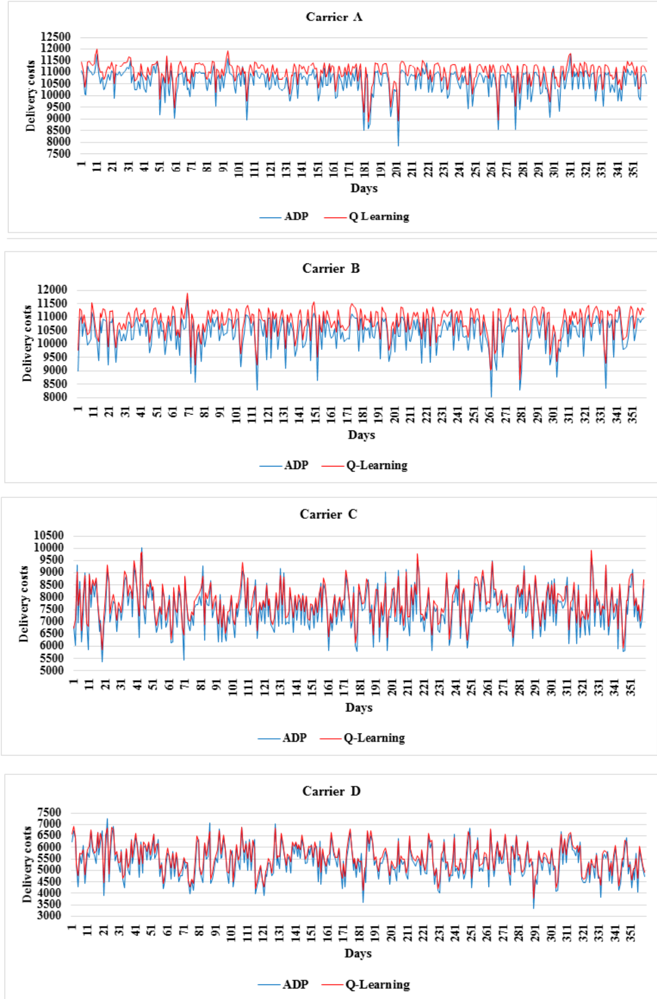

Fig.5 Total delivery costs of Carrier A, B, C, and D in normal traffic setting

6. CONCLUSIONS AND FUTURE WORK

This paper presented the general framework of ADP models in evaluating joint delivery with UCC within urban distribution systems. ADP gives more than 3.5% reduction (on average) in delivery cost as compared to Q-learning for the random demand experiment. The results obtained in the paper show that the combination of MAS and ADP could contribute a lot to both simulation models and optimization algorithms.

The study of MAS-ADP model is still in the rise period especially in city logistics area. We hope that the readers would have a preliminary understanding about either the ADP models, or its behaviour within MAS through this paper. As general research framework illustrated, other dynamic environment setting (such as dynamic travel time and dynamic customers) will be evaluated in the future. Similarly, ADP models will be developed for other stakeholders (shippers, administrator, and residents) and interaction within multi-agents environment will be done in the future. Evaluating multi-policies within MAS using ADP also interested to investigate in the future work.

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