*Electronics, Communications and Networks*
*A.J. Tallón-Ballesteros et al. (Eds.)*

*© 2024 The authors and IOS Press.*
*This article is published online with Open Access by IOS Press and distributed under the terms of the Creative Commons Attribution Non-Commercial License 4.0 (CC BY-NC 4.0).*
*doi:10.3233/FAIA231250*

# A Numerical Planning-Based Method for Logistics Transportation

Dongning RAO[a], Mingtao XUAN[a], Ruishi LIANG[b,1] and Zhenghui XU[a]
[a]*School of Computer Science, Guangdong University of Technology, Guangzhou, China*
[b]*School of Computer Science, University of Electronic Science and Technology of China, Zhongshan Institute, Zhongshan, China*

**Abstract.** The primary objective of logistics transportation vehicle scheduling is to guide transportation vehicles to complete logistics tasks in the shortest possible time while minimizing logistics costs. However, traditional research in logistics transportation vehicle scheduling has been criticized for its narrow focus, limited consideration of constraints, and often sub-optimal route planning, which hinder its practical applicability. To address these issues, we propose an AI Planning method to simulate logistics transportation vehicle scheduling scenarios. We utilize the PDDL language to construct standard planning tasks, and then employ the state-of-the-art planner to solve these tasks, generating planning solutions which are used as vehicle scheduling schemes. The experimental results demonstrate that our proposed method is capable of generating scheduling schemes in a relatively short time, guiding transport vehicles to complete logistics transportation tasks.

**Keywords.** Artificial Intelligence, numerical planning, logistics transportation, vehicles scheduling

## 1. Introduction

With the rapid development of the economy, significant changes have occurred in the market environment and industrial structure. This transformation requires advanced logistics transportation as a support, and logistics transportation vehicle scheduling is a crucial component of logistics transportation optimization. Yunmei Yuan et al. proposed an optimization strategy based on deep reinforcement learning [1]. Zhaolei He et al. proposed an Improved Life-cycle Swarm Optimization (ILSO) algorithm to help companies reduce costs [2]. Bo Dong et al. investigated the joint optimization and visualization of inventory transportation in agricultural logistics based on ACA [3].

As an important branch of the field of artificial intelligence, AI planning has been applied in many domains. Jiulong Han et al. modeled the warehouse scheduling domain as a planning problem [4]. Dongning Rao et al. integrated probabilistic planning into the robot operating system [5]. Ruishi Liang et al. proposed a novel goal

[1]Corresponding Author: liangruishi@foxmail.com

ordering algorithm for incremental planning, making incremental planning more convenient for real-world applications [6].

In this paper, we propose a multi-objective, multi-vehicle scheduling method based on numerical planning that considers both traffic congestion and vehicle energy consumption. We use the PDDL2.1 [7] language to describe three transportation vehicle scheduling problems and solve them using the Metric-FF [8] planner. Through the planner's solutions, we can quickly find scheduling schemes that minimize both time and energy consumption in various scenarios.

The background of AI Planning and an abstract representation of the logistics and transportation vehicle problem are presented in Section 2. In Section 3 we describe the methodology for domain knowledge extraction and domain action construction for the logistics transportation vehicle scheduling problem. Finally, in Sections 4 and 5, we present the details of our experiments and the results obtained.

## 2. Background

### *2.1. AI Planning*

AI Planning involves the continuous deduction of actions within a given action framework to solve real-world problems and ultimately achieve objectives. Classical planning [9] is not only a significant branch of AI planning but also its foundation. Numerical planning [10], building upon the base of classical planning, incorporates precise optimization of numerical variables within problem-solving processes. In this paper, we describe planning problems using the PDDL2.1 language. A numerical planning problem can be represented as a six-tuple $P = \langle F, I, G, A, c, f \rangle$, where $F$ is a finite set of atoms describing object properties or relationships. $I \subseteq F$ represents the initial state of the problem, while $G \subseteq F$ represents the goal state. A is a set of actions, The set $c$ represents the costs associated with actions, where $c(a) \in c$ indicates the cost required to execute action a. Lastly, $f$ signifies the set of numerical variables within the problem.

### *2.2. Logistics Transportation Vehicle Scheduling*

Based on variations in the number of goods depots and transport vehicles, we can categorize logistics transportation vehicle scheduling problems into the following scenarios:

- Single Depot Distribution: This scenario includes one depot, one transport vehicle, and multiple destinations.
- Multi-Depot Distribution: This scenario includes multiple depots, multiple transport vehicles, and multiple destinations.
- Contribution Point Distribution: This scenario involves a two-tier distribution network with contributions. The first tier transports goods from depots to contribution points, and the second tier transports goods from contribution points to destinations.

Based on the above three scenarios, we abstract the logistics transportation vehicle scheduling problem into the simplified scenario shown in Figure 1.

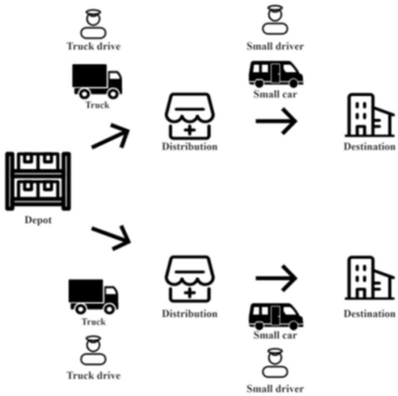


**Figure 1.** Logistics Transportation Vehicle Scheduling Diagram

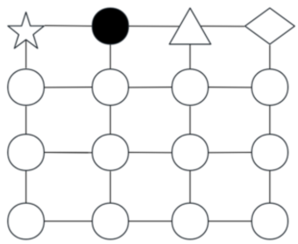

**Figure 2.** Abstract Transportation Route Diagram

The transportation route is described with an abstract diagram shown in Figure 2. Straight lines represent that locations at both ends are reachable, white circles indicate passable intersections, black circles denote congested intersections, five-pointed stars represent depots, diamonds symbolize contribution points, and triangles denote the destinations for transporting goods.

## 3. Logistics Transportation Vehicle Scheduling Model

### *3.1. Domain Knowledge Extraction*

In AI Planning, constants represent fixed and unchanging entities. Objects represent specific entities within the domain, and different objects have different types. Predicates are used to describe specific information about different objects in a state.

Based on the description of scenarios in the logistics transportation vehicle scheduling problem in the previous section, we define four parent object classes: location, car, driver, and package. Since there are different types of locations and transportation vehicles in the scheduling scenario, we define four sub-types of location, including go-area, stop-area, destination, contribution, and depot, representing passable intersections, congested intersections, destinations, goods distribution points, and depots, respectively. Details of other predicates are presented in Figure 3.

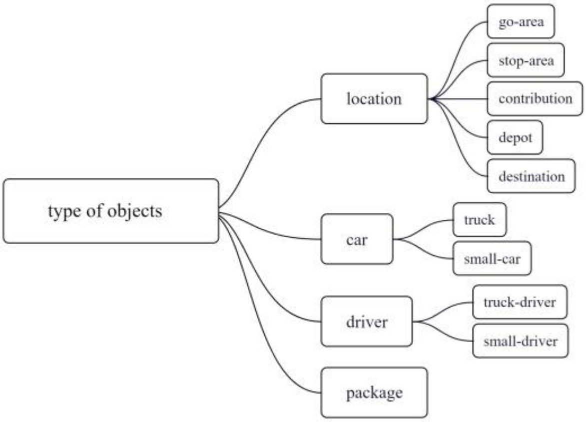


**Figure 3.** Type of objects structure diagram

To better represent the different states in the logistics transportation vehicle scheduling scenario, we have defined several predicates to describe information about different objects in the scenario. Table 1 shows the 12 predicates we have constructed for the logistics transportation vehicle scheduling problem. **located-east** is a static predicate used to express the location relationship between different locations. **at-c**, **at-p**, and **at-d** are used to represent the real-time location information of transportation vehicles, goods and drivers during transportation. **carry** indicates the carrying information of the goods. **no-drive** and **can-drive** represent the driving information of the vehicle. **busy** and **free** represent traffic conditions information at the intersection.

**Table 1.** The definition of predicates

| Predicate | |
|---|---|
| (located-east ?l1 - location ?l2 - location) | (at-d ?d - driver ?l - location) |
| (located-west ?l1 - location ?l2 - location) | (carry ?c - car ?p - package) |
| (located-north ?l1 - location ?l2 - location) | (no-drive ?c - car) |
| (located-south ?l1 - location ?l2 - location) | (can-drive ?c - car ?d - driver) |
| (at-c ?c - car ?l - location) | (busy ?l - location) |
| (at-p ?p - package ?l - location) | (free ?l - location) |

### *3.2. Domain Action Construction*

In AI Planning, the change in state is achieved through the execution of actions. To accommodate state changes in the logistics transportation vehicle scheduling scenario, we have defined 20 domain actions, such as load, drive-west, move-north, etc. Load is used to indicate the loading of goods onto trucks. When this action is executed, the location information of the goods and the loading information of the vehicles will change. Drive-west is used to represent the movement of trucks' positions. After executing this action, the location information of the truck will change. Table 2 shows the definition details of partial actions.

**Table 2.** The definition of partial actions

| Action |
|---|
| (:action load<br>:parameters (?c - truck ?d - truck-driver ?p - package ?l - depot)<br>:precondition (and (at-c ?c ?l) (at-p ?p ?l) (can-drive ?c ?d))<br>:effect (and (carry ?c ?p) (not (at-p ?p ?l)) (increase (total-cost) 5))<br>)<br>(:action drive-west<br>:parameters (?c - truck ?d - truck-driver ?from - location ?to - location)<br>:precondition (and (at-c ?c ?from) (located-west ?from ?to) (can-drive ?c ?d) (free ?to))<br>:effect (and (at-c ?c ?to) (not (at-c ?c ?from)) (increase (total-cost) (truck-time ?c)))<br>) |

In addition, based on the idea of numerical planning, we also define a numerical cost function, *total-cost*, where each action has a corresponding cost, and the value of *total-cost* increases when the action is executed. For example, the execution of the action load will increase the *total-cost* by 5.

## 4. Experiment

In this section, we create domain files and problem files based on the logistics and transportation vehicle scheduling model. All the experiments are done in Ubuntu 20.04 operating system with Intel® Xeon(R) W-2123 CPU @ 3.60GHz and 32GB of RAM. We use Metric-FF planner to solve the problems and set a solution time of 1 minute for each problem.

In order to solve different real-life logistics and transportation vehicle scheduling problems, we consider the following two scenarios:

- Having one depot, one goods distribution point, and multiple destinations.
- Having one depot, multiple goods distribution points, and multiple destinations.

For scenario 1, we use the traffic condition scenario shown in Figure 2. In this scenario, *loc1* represents the depot, *loc4* is the distribution point, *loc3* is the destination, *loc2* is the congested intersection, and the rest of the locations are passable intersections. In the initial state, there is a truck *t1* and a truck driver *td1* at *loc1*, and there is a small transport vehicle *s1* and a small transport vehicle driver *sd1* at *loc4.* For Scenario 2, we add a distribution point *loc13* and a destination *loc9* to Scenario 1, and set *loc11* to a congested intersection.

## 5. Result

For the above two scenarios, we describe them as PDDL problem files and solve them using the Metric-FF planner. The left and center columns of Figure 4 are the plans for Scenarios 1 and Scenarios2. According to the optimal planning solution found by the planner, we use the planning solution as the scheduling scheme in this scenario.

Considering that there are some special cases in the logistics transportation vehicle scheduling problem, such as the transportation vehicle does not have enough fuel to complete the whole transportation process. Therefore, we add the fuel replenishment action on the basis of the above model and add numerical judgment conditions for the preconditions of the transportation vehicle movement action. The action drive-west adds the numerical judgment precondition (>= (*truck-fuel-have ?c*) (*truck-fuel-need ?c*)) to the above model, so that the action can be executed only if (*truck-fuel-have ?c*) is numerically greater than or equal to (*truck-fuel-need ?c*). And add (decrease (*truck-fuel-have ?c*) *(truck-fuel-need ?c*)) to the effect so that whenever the action is executed, (*truck-fuel-have ?c*) is numerically decremented by the value of (*truck-fuel-need ?c*). To validate the modified model, we make the following changes in Scenario 2: we designate *loc5* as a refueling point and add a destination, *loc16*. The plan for Scenario 3 is shown in the right column of Figure 4. By validating the planning solutions, it can be observed that the plans generated by the Metric-FF planner effectively guide the vehicles to refuel in a timely manner when their fuel levels are insufficient, ensuring the completion of transportation tasks.

```
ff: found legal plan as follows
step    0: GET-IN-TRUCK T1 TD1 LOC1
        1: LOAD T1 TD1 P1 LOC1
        2: GET-IN-SMALL S1 SD1 LOC4
        3: DRIVE-SOUTH T1 TD1 LOC1 LOC5
        4: DRIVE-EAST T1 TD1 LOC5 LOC6
        5: DRIVE-EAST T1 TD1 LOC6 LOC7
        6: DRIVE-NORTH T1 TD1 LOC7 LOC3
        7: DRIVE-EAST T1 TD1 LOC3 LOC4
        8: UNLOAD T1 TD1 P1 LOC4
        9: DRIVE-WEST T1 TD1 LOC4 LOC3
       10: DRIVE-SOUTH T1 TD1 LOC3 LOC7
       11: DRIVE-WEST T1 TD1 LOC7 LOC6
       12: PICK-UP S1 SD1 P1 LOC4
       13: DRIVE-WEST T1 TD1 LOC6 LOC5
       14: DRIVE-NORTH T1 TD1 LOC5 LOC1
       15: MOVE-WEST S1 SD1 LOC4 LOC3
       16: PICK-DOWN S1 SD1 P1 LOC3
       17: MOVE-EAST S1 SD1 LOC3 LOC4
plan cost: 36.000000
```

```
ff: found legal plan as follows
step    0: GET-IN-TRUCK T1 TD1 LOC1
        1: LOAD T1 TD1 P2 LOC1
        2: LOAD T1 TD1 P1 LOC1
        3: GET-IN-SMALL S2 SD2 LOC13
        4: MOVE-NORTH S2 SD2 LOC13 LOC9
        5: DRIVE-SOUTH T1 TD1 LOC1 LOC5
        6: DRIVE-SOUTH T1 TD1 LOC5 LOC9
        7: DRIVE-SOUTH T1 TD1 LOC9 LOC13
        8: UNLOAD T1 TD1 P2 LOC13
        9: UNLOAD T1 TD1 P1 LOC13
       10: DRIVE-NORTH T1 TD1 LOC13 LOC9
       11: DRIVE-NORTH T1 TD1 LOC9 LOC5
       12: DRIVE-NORTH T1 TD1 LOC5 LOC1
       13: MOVE-SOUTH S2 SD2 LOC9 LOC13
       14: PICK-UP S2 SD2 P2 LOC13
       15: MOVE-NORTH S2 SD2 LOC13 LOC9
       16: PICK-DOWN S2 SD2 P2 LOC9
       17: MOVE-SOUTH S2 SD2 LOC9 LOC13
       18: PICK-UP S2 SD2 P1 LOC13
       19: MOVE-EAST S2 SD2 LOC13 LOC14
       20: MOVE-NORTH S2 SD2 LOC14 LOC10
       21: MOVE-NORTH S2 SD2 LOC10 LOC6
       22: MOVE-NORTH S2 SD2 LOC6 LOC2
       23: MOVE-EAST S2 SD2 LOC2 LOC3
       24: PICK-DOWN S2 SD2 P1 LOC3
       25: MOVE-WEST S2 SD2 LOC3 LOC2
       26: MOVE-SOUTH S2 SD2 LOC2 LOC6
       27: MOVE-SOUTH S2 SD2 LOC6 LOC10
       28: MOVE-SOUTH S2 SD2 LOC10 LOC14
       29: MOVE-WEST S2 SD2 LOC14 LOC13
plan cost: 108.000000
```

```
ff: found legal plan as follows
step    0: GET-IN-TRUCK T1 TD1 LOC1
        1: LOAD T1 TD1 P2 LOC1
        2: LOAD T1 TD1 P3 LOC1
        3: LOAD T1 TD1 P1 LOC1
        4: GET-IN-SMALL S2 SD2 LOC13
        5: MOVE-EAST S2 SD2 LOC13 LOC14
        6: MOVE-EAST S2 SD2 LOC14 LOC15
        7: DRIVE-SOUTH T1 TD1 LOC1 LOC5
        8: DRIVE-SOUTH T1 TD1 LOC5 LOC9
        9: DRIVE-SOUTH T1 TD1 LOC9 LOC13
       10: UNLOAD T1 TD1 P1 LOC13
       11: UNLOAD T1 TD1 P2 LOC13
       12: UNLOAD T1 TD1 P3 LOC13
       13: DRIVE-NORTH T1 TD1 LOC13 LOC9
       14: DRIVE-NORTH T1 TD1 LOC9 LOC5
       15: ADD-TRUCK-FUEL T1 TD1 LOC5
       16: DRIVE-NORTH T1 TD1 LOC5 LOC1
       17: MOVE-WEST S2 SD2 LOC15 LOC14
       18: MOVE-WEST S2 SD2 LOC14 LOC13
       19: PICK-UP S2 SD2 P2 LOC13
       20: PICK-UP S2 SD2 P3 LOC13
       21: PICK-UP S2 SD2 P1 LOC13
       22: MOVE-EAST S2 SD2 LOC13 LOC14
       23: MOVE-EAST S2 SD2 LOC14 LOC15
       24: MOVE-EAST S2 SD2 LOC15 LOC16
       25: PICK-DOWN S2 SD2 P3 LOC16
       26: MOVE-WEST S2 SD2 LOC16 LOC15
       27: MOVE-NORTH S2 SD2 LOC15 LOC11
       28: MOVE-WEST S2 SD2 LOC11 LOC10
       29: MOVE-WEST S2 SD2 LOC10 LOC9
       30: PICK-DOWN S2 SD2 P2 LOC9
       31: MOVE-NORTH S2 SD2 LOC9 LOC5
       32: ADD-SMALL-FUEL S2 SD2 LOC5
       33: MOVE-EAST S2 SD2 LOC5 LOC6
       34: MOVE-EAST S2 SD2 LOC6 LOC7
       35: MOVE-NORTH S2 SD2 LOC7 LOC3
       36: PICK-DOWN S2 SD2 P1 LOC3
       37: MOVE-WEST S2 SD2 LOC3 LOC2
       38: MOVE-SOUTH S2 SD2 LOC2 LOC6
       39: MOVE-WEST S2 SD2 LOC6 LOC5
       40: ADD-SMALL-FUEL S2 SD2 LOC5
       41: MOVE-SOUTH S2 SD2 LOC5 LOC9
       42: MOVE-SOUTH S2 SD2 LOC9 LOC13
plan cost: 174.000000
```

**Figure 4.** Plans for three Scenarios

## 6. Conclusion

In this paper, we propose an AI Planning method for solving the logistics transport vehicle scheduling problem that includes many influencing factors such as fuel replenishment, traffic congestion and multiple destinations. Our model makes full use of the numerical expressions in PDDL2.1, especially taking the fuel consumption of transport vehicles into account. We used the Metric-FF planner to solve the scenarios we designed. Guided by the optimal planning solutions, logistics vehicles can complete transportation tasks in the shortest possible time.

## Acknowledgement

The authors acknowledge the Major Science and Technology Foundation of Zhongshan City (2019B2006, 2019A40027, 2021A1003), the First-Class Course Program of Guangdong Province (YLKC202202), the Youth Innovation Talent Program of Guangdong Province (2022KQNCX152, 2022KQNCX153), the Science and Technology Commissioner Project of Guangdong Province (GDKTP2021025700), the Innovation Research Group of UESTC Zhongshan Institute (420YTS03). We are also very grateful for the support and encouragement from the School of Computer Science at Guangdong University of Technology(GDUT).

## References

[1] Yuan Y, Li H, Ji L. Application of Deep Reinforcement Learning Algorithm in Uncertain Logistics Transportation Scheduling. Comput Intell Neurosci. 2021 Sep 25;2021:5672227.
[2] He Z, Zhang M, Chen Q, Chen S, Pan N. Optimization of heterogeneous vehicle logistics scheduling with multi-objectives and multi-centers. Sci Rep. 2023 Aug 29;13(1):14169.
[3] Dong B, Duan M, Li Y. Exploration of Joint Optimization and Visualization of Inventory Transportation in Agricultural Logistics Based on Ant Colony Algorithm. Comput Intell Neurosci. 2022 Jun 15;2022:2041592.
[4] J. Han, R.Liang,H. Yao and H. Yao, Intelligent Warehousing based on numerical heuristic planning, 2023 4th International Conference on Electronic Communication and Artificial Intelligence (ICECAI), Guangzhou, China, 2023: 353-357
[5] Rao, D., Hu, G., & Jiang, Z. PRobPlan: A Framework of Integrating Probabilistic Planning Into ROS. IEEE Access, 8, 2020:106516-106530.
[6] Liang, R., Mao, M., Ma, H. et al. A new goal ordering for incremental planning. J Supercomput 76, 2020:3713 – 3728.
[7] M. Fox, D. Long. PDDL2.1: An Extension to PDDL for Expressing Temporal Planning Domains. The Journal of Artificial Intelligence Research. 2003:61-124
[8] J. Hoffmann. The Metric-FF Planning System: Translating ``Ignoring Delete Lists'' to Numeric State Variables. The Journal of Artificial Intelligence Research. 2003: 291-341
[9] Lipovetzky, N. Structure and inference in classical planning. AI Access. 2014
[10] Alfonso E. Gerevini, Alessandro Saetti, Ivan Serina. An approach to efficient planning with numerical fluents and multi-criteria plan quality. Artificial Intelligence 172.8-9. 2008:899-944