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# Simulation Analysis of a Highway DNN for Autonomous Forklift Dispatching

**Prashant Sankaran, Maojia P. Li, Michael E. Kuhl,**
**Raymond Ptucha, Amlan Ganguly, Andres Kwasinski**
**Rochester Institute of Technology**
**Rochester, NY 14623, USA**

## Abstract

With the proliferation of autonomous vehicles in warehouse applications, there are several challenges that face researchers including precision indoor localization, navigation, obstacle avoidance, path planning, and task selection decisions. This paper addresses the issue of task selection decision. Specifically, we develop a deep learning methodology for task selection for fleet of autonomous vehicles in a warehouse environment. The autonomous vehicles select a task from a list of tasks, considering current vehicle traffic, potential travel paths, and the task potential task locations. We implement a highway deep neural network (DNN) for the task selection process. To evaluate the methodology, we conducted a simulation-based experiment to generate various scenarios and test the capabilities of the DNN. The results of the simulation-based experiment show that our deep learning method performs well under the given conditions.

## Keywords
Autonomous Vehicles, Deep Learning, Material Handling, Dispatching

## 1. Introduction

In recent years, a growing use of autonomous vehicles has been observed. Specifically, the application of autonomous vehicles for warehouse operations has increased due to their flexibility and efficiency, the reduction of ergonomic issues, and recent successes of the autonomous driving technology. Although the autonomous vehicle brings together a new set of technological upgrades, there are a host of complex challenges that need to be addressed including navigation, path planning, obstacle avoidance, localization, sensory systems, and task selection under a multi-vehicle environment. This paper focuses on the task selection problem in a warehouse environment where a fleet of vehicles is given a set of tasks that needs to be completed. When a vehicle become available, the vehicle determines the next task that it will perform in light of the current warehouse situation (such as, task locations and priorities, locations and status of other vehicles, and alternative available travels path). To address this problem, we have developed a deep learning-based task selection methodology for autonomous vehicles in a warehouse. We present this methodology and conduct a simulation study to demonstrate the capabilities and limitations.

Despite the considerable amount of recent research on autonomous vehicle navigation and path planning, few researchers have focused on the task assignment problem. Euchi et al. (2010) & Drexl (2012) consider the task selection problem as a routing problem and introduce various optimization methods. In addition, Fauadi et al. (2013) address the task selection problem in the multi-agent environment through an intelligent combinatorial auction methodology. Further, reinforcement learning based methods have been applied to task selection for use in applications such as container terminals (Jeon et al., 2011) and warehouses (Estanjini et al., 2011, Li et al., 2018). Estanjini et al. (2011) uses a localization engine based on a wireless network and an actor-critic-type policy optimization for forklift dispatching. The current direction of our research is similar in focus but employs a deep learning-based methodology.

## 2. Methodology

To address the task selection problem for a fleet of autonomous vehicles in a warehouse, we develop a deep learning based decision-making framework where these decisions are based on the current state of a dynamic environment. Figure 1 represents an example of a portion (two aisles) of a warehouse, where pallet storage locations make up the set of potential task locations for storage or retrieval of a pallet. Autonomous vehicles will operate in the aisles of the warehouse to select a task involving picking up and then dropping off a pallet. As with delivery, dropping off a pallet must always follow picking up a pallet from a storage location, the task selection problem is narrowed down to which pallet to pick up next when the autonomous vehicle becomes available.

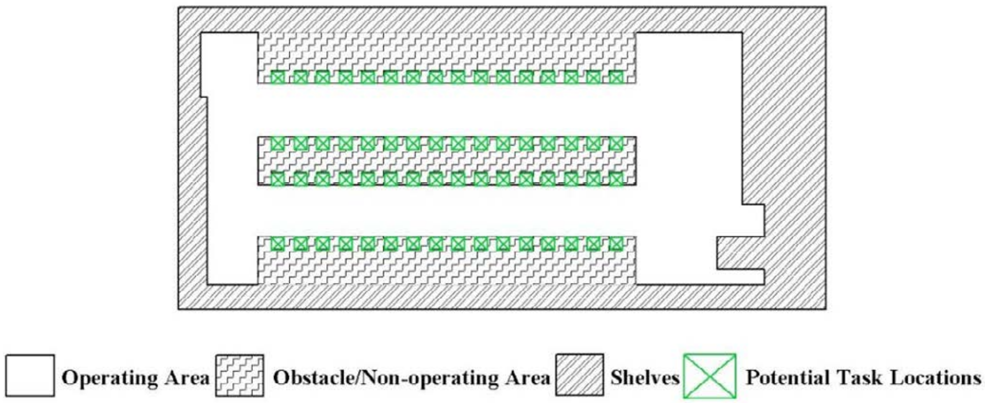


Figure 1: Warehouse layout and potential task locations

The framework of our deep learning methodology is shown in Figure 2. The state inputs are images representing the current condition of the warehouse. The pixels of the image are translated into grid (matrix) of values indicating the vehicle locations, task locations, obstacles, and empty space that a vehicle can occupy. At the time that a vehicle needs to select a task to perform, the current state input image is sent to the deep learning model. The deep learning model determines the task that the vehicle should be assigned. The dispatching system monitors and executes the assignment decisions. To train the deep learning algorithm a hierarchical search algorithm is used to generate the “best” task assignment. A set of state input images are utilized to train the deep learning model to produce good task selection decisions.

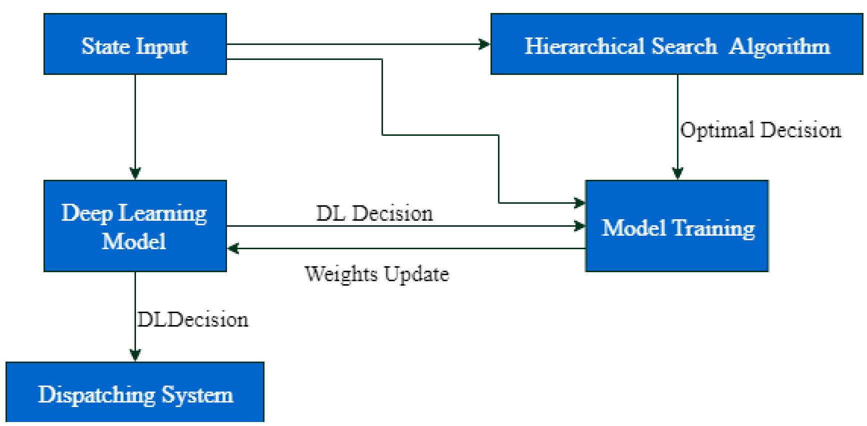


Figure 2: Deep learning based decision-making framework

The deep learning model implemented in this research is based on the highway deep neural network (DNN) model introduced by Srivastava et al. (2015). A highway architecture is chosen based on its potential to improve learning performance on a large data. The DNN approach proposed solves the task selection problem as a multi-class classification problem, where each potential task location is considered a class and the score for each class is computed on a single forward propagation of input data making the task decision problem independent of the search space. The network architecture used is shown in Figure 3. The deep learning model architecture consists of five highway network modules, a 3x3x128 convolution layer, two fully connected layers with 2048 nodes each, and an output layer with 64 nodes. The highway network module consists of two parts. First, the five 3x3x64 dimensional convolutional layers extract the important features from the image, such as task locations, shelves, and aisles. The next part of the highway net module is a 3x3x64 dimensional convolutional layer that performs a spatial reduction process. Then, the fully connected layers are used to determine the final task selection decision. The 64 nodes in the output layer correspond to the 64 potential task locations. The output of each class is interpreted as the score of the corresponding task. The model chooses the task that has the largest score.

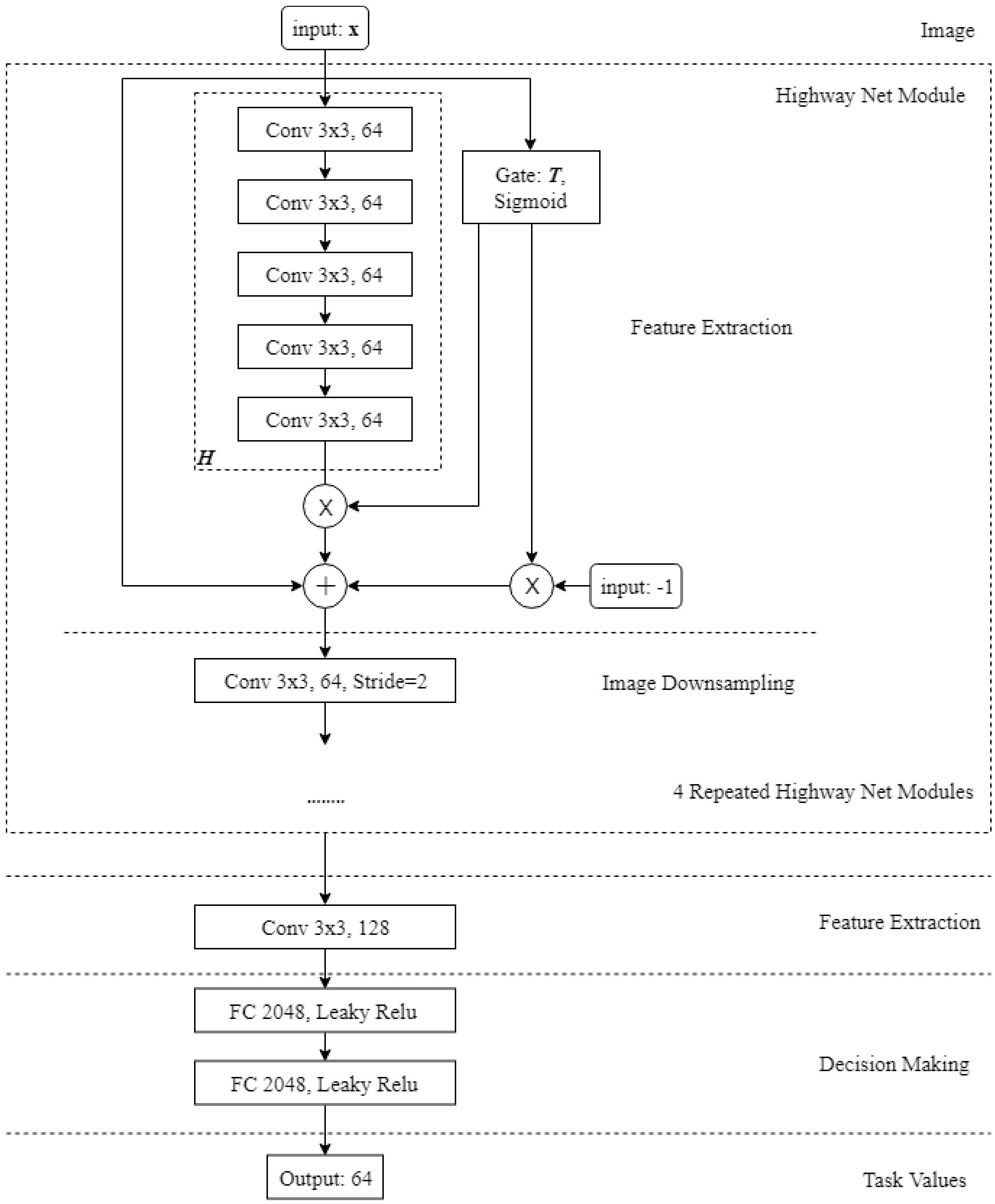


Figure 2: Highway deep neural network architecture

The highway network layer output can be mathematical expressed as (Srivastava et al., 2015):

$$\hat{\boldsymbol{y}} = \boldsymbol{H}(\boldsymbol{x}, \boldsymbol{W_H}) \cdot \boldsymbol{T}(\boldsymbol{x}, \boldsymbol{W_T}) + \boldsymbol{x} \cdot \boldsymbol{C}(\boldsymbol{x}, \boldsymbol{W_c}) \tag{1}$$

where $\hat{\boldsymbol{y}}$ is the layer output, $\boldsymbol{H}(\cdot)$ is the non-linear activation function parameterized by $\boldsymbol{x}$ (input) & $\boldsymbol{W_H}$ (weights). The transformation gate, $\boldsymbol{T}(\cdot)$, expresses how much of output is produced by transforming the input. The carry gate, $\boldsymbol{C}(\cdot)$, indicates how much output should be carried to the next layer. In our case, the carry gate is

$$\boldsymbol{C}(\cdot) = \boldsymbol{1} - \boldsymbol{T}(\cdot).$$

To train the DNN, a hierarchical search algorithm computes the optimal decision (ground truth) for a state input. The algorithm considers the travel distance from the vehicle to the task as well as the traffic condition in the aisle. A deep learning model estimates the optimal decision and compares it to the ground truth. The error from ground truth and estimation are used for model training. The weights of the DNN are then updated based on a backward propagation process.

The loss function used for our network training is the hinge loss function,

$$L(\boldsymbol{y}) = \max(0, \boldsymbol{1} - \hat{\boldsymbol{y}} * \boldsymbol{y}) \tag{2}$$

where $\boldsymbol{y}$ is a Boolean variable indicating whether the corresponding class is selected by the hierarchical search algorithm. This function directly penalizes the actual output value of the predicted class rather than the index value as is the case of a traditional support vector machine.

The novel contribution to this approach stems from the fact that the determination of our high traffic aisles is purely based on task location and their status and not on any other sensory inputs. This provides the leverage to scale up the system without increasing data transfer or computational loads. Further, the framework expands beyond the traditional static deep learning framework encompassing the feasibility of a feedback learning approach based on prediction confidence. This enables the model to continue training and update the existing model. The adaptation of the model to new layout configurations involves a self-training process where different scenarios are auto-generated for model training. The only information required to accommodate the change to a new environment is the image of the new layout configuration and potential task locations with corresponding aisle identification.

## 3. Simulation Experiments

The performance of the proposed deep learning framework is evaluated through simulation experiments. A pre-trained deep learning model is used to dispatch multiple autonomous vehicle in a warehouse environment. The warehouse layout is generated based on a cost map using SLAM algorithm and LiDAR equipped on a robot. Figure 1 demonstrates the layout of the warehouse as well as the potential task locations. At this stage, we only consider two aisles of the warehouse. At the beginning of a trial, the model randomly generates a specified number of tasks from the potential locations. The initial location of a vehicle is randomly selected within the operating area.

Figure 4 provides two sample input images for the DNN. Sample 1 represents a system with 2 vehicles and 3 pending tasks. The vehicle that needs to make a decision is highlighted in blue. The other vehicle's location is not demonstrated in the input, but its current destination is marked in light gray. This is because our goal is to avoid dispatching too many vehicles to the tasks in the same aisle so that other vehicles' locations are less relevant to make a decision. A hierarchical dispatching algorithm that considers both traffic condition and travel distance is implemented to generate the "ground truth" class for training purposes. The algorithm first finds the aisle(s) having the smallest number of pickup tasks assigned to other vehicles, and then select the task that is closest to the vehicle in that aisle.

For the current study, we have taken 2 different test cases: 3 pending tasks and 5 pending tasks with 4 vehicles (refer to Table 1). The study assumes high task volumes thereby justifying a larger than usual vehicle quantities to cater the lead times.

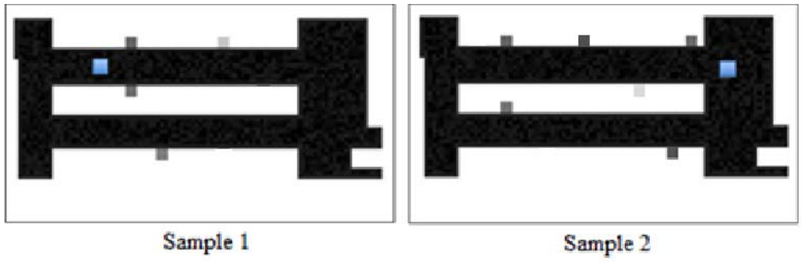


Figure 4. Two samples showing vehicle location (blue), pending tasks (dark gray), other vehicles' destinations (light gray), obstacles (white), and available space (black) when having 3 (Sample 1) and 5 (Sample 2) pending tasks.

Table 1. Simulation experiment

| Scenario | Parameters | |
|---|---|---|
| | Number of vehicles | Number of Pending Tasks |
| 1 | 4 | 3 |
| 2 | 4 | 5 |

## 4. Results

Table 2 summarizes training and testing accuracy of the DNN model. The DNN is trained for 50 epochs for Scenario 1 and 25 epochs for Scenario 2 with a batch size of 10 based on 32,000 training samples. In each epoch, the entire training dataset is passed through the DNN model. The difference in training epochs is due to a difference in training saturation monitored through loss value. After each epoch, the trained model is then tested on 50,000 randomly generated samples. Such a training and testing procedure avoid the overfitting issue. The accuracy is measured by the frequency of DNN making the same decision as the hierarchical dispatching rule. Figure 5 shows the training accuracy for Scenario 2 is close to 100% after 18 epochs and the testing accuracy goes above 90% after 18 epochs. The high testing accuracy indicates that the deep learning model can make the same decision as the hierarchical algorithm in most cases. The final training accuracies in both scenarios are both close to 100%. The testing accuracy in scenario 1 is slightly higher than scenario 2.

Table 2. Training and testing accuracy for four scenarios

| Scenario | Parameters | | Performance Measure | |
|---|---|---|---|---|
| | Number of vehicles | Number of Pending Tasks | Training Accuracy | Testing Accuracy |
| 1 | 4 | 3 | 99.9 | 94.0 |
| 2 | 4 | 5 | 100.0 | 93.1 |

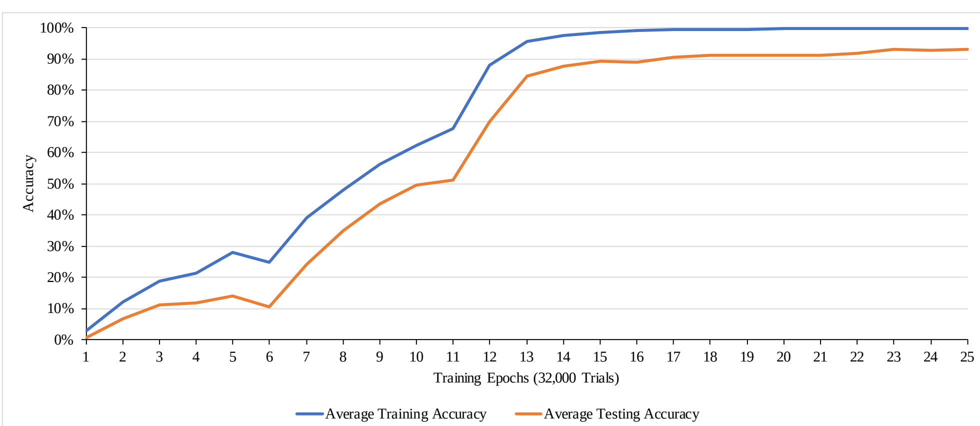


Figure 5: Average Training vs. Testing Accuracy for Scenario 2

Further, we compare the performances of the DNN model and a Shortest Travel Distance (STD) rule in terms of dispatching the vehicle to a lower traffic aisle. Table 2 summarizes the results. The performance is measured by the number of vehicles (traffic intensity) in the selected aisle after dispatching the vehicle to the aisle. The DNN model outperforms STD rule in both scenarios. As the STD rule always dispatch the vehicle to the closest pickup location, there are, on average, 2.48 vehicles in the selected aisle. In contrast, the DNN model dispatch the vehicle to the aisle with less traffic intensity. The most significant improvement is that DNN model reduces TISA from 2.48 to 1.80 in scenario 2.

Table 2. Average traffic intensity in selected aisle (TISA) for DNN model and STD rule

| | Parameters | | TISA | |
|---|---|---|---|---|
| Scenario | Number of vehicles | Number of Pending Tasks | DNN Model | STD Rule |
| 1 | 4 | 3 | 1.93 | 2.48 |
| 2 | 4 | 5 | 1.80 | 2.48 |

## 5. Conclusion

In conclusion, we have presented a deep learning methodology for task selection by an autonomous vehicle in a warehouse environment. The results of the simulation-based experiment indicate that the method can consistently select the closest task in a low traffic aisle given a random set of task location at a high level of performance. This illustrates the capability of the DNN approach to cater multiple attribute decision making: shortest travel distance and traffic. During the study it was observed that the highway network architecture used aided in improving the model training, and the computation time is independent of the search space as expected which is believed to make a difference in a larger and more complex scenario. It is to be noted that the performance of the proposed DNN method like any supervised learning approach is dependent on the availability of good labeled training data and model selection, and training procedure. Our future work includes extending the study to include more complex layouts, decision attributes and lastly, apply the methodology to a physical warehouse system for validation.

## 6. Acknowledgements

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