A market-based approach for dynamic vehicle deployment planning using radio frequency identification (RFID) information

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1. Introduction

For the past several decades, advances in manufacturing and supply chain management have improved to a great extent the business performance of companies. Nonetheless, a gap still exists between plan and execution because of dynamics, such as various unexpected disruptions and uncertainties, in business operations. Two important capabilities are essential to fill this gap: one is to quickly detect the operational dynamics in business operations, and the other is to effectively share that information with business partners.

Huang et al. (2003) contended that many problems in dynamic operational environments have their resolutions in timely information sharing among operational members. For the dimension of timeliness, lateness and inaccuracy in sharing information are identified as one of the major causes of performance degradation in decision-making for manufacturing companies (Hong-Minh et al., 2000; Lee et al., 1997), while the information exchange in real-time has been proposed to improve operational performance (Karaesmen et al., 2002). Thus, the requirements for decision-making systems in order to achieve management goals are that they should be adaptable and flexible enough to process real-time information and responsive to the dynamic environment.

Recently, radio frequency identification (RFID) technologies have been widely used in various logistical operations where limitations exist due to the inaccuracies and delays of product identification (Angeles, 2005; Chow et al., 2006; McFarlane et al., 2003; Saygin, 2007; Wilding and Delgado, 2004). Several companies have been investigating how RFID can be used for improving their operational performance (Hou and Huang, 2006; Kim et al., 2005, 2008; Thiesse et al., 2005). Potential benefits of the RFID would be as follows: (1) make decisions more efficiently and effectively using real-time data, (2) perform routine and manual tasks better with reduced cost or possibly eliminate them, and (3) feed real-time information of operational transactions to corporate-level information systems for better planning and execution (Datta and Viguier, 2000; Hanebeck and Tracey, 2003; Walker, 2005).

Outbound logistics business of the automotive industry has grown significantly for the last decade, and transshipment hub management, such as shipment yard, vehicle distribution centers or port, is one of the most important processes (Mattfeld and Kopfer, 2003). For the transshipment hub management, decision-making models have been developed, such as facility location and layout (Domschke and Kräspin, 1997; Klose and Drexl, 2005), routing and scheduling (Christiansen et al., 2004; Vis and Koster, 2003), the design of storage space allocation (Cassady and Kobza, 1998;
Kim and Park, 2003), and shipment loading (Agbegha et al., 1998; Tadei et al., 2002). Not much study has been conducted to directly address the management or operational decision-making for shipment yard of an automobile manufacturer.

Mattfeld and Koprfer (2003) developed an automated planning and scheduling system to support operations for the transportation of finished vehicles in a transshipment hub by integrating manpower planning and inventory control using a two-stage hierarchical approach.

Mattfeld and Orth (2006) presented a planning model of transportation and storage capacity in a vehicle transshipment hub using a construction heuristic (greedy approach) that assigns vehicles to storage locations.

Yee et al. (2008) and Kim et al. (2008) presented an automobile shipment yard decision-making framework that is developed on top of an RFID-enabled wireless communication system in conjunction with order-to-delivery business model in order to process the dynamics of shipment yard operations and make decisions in real-time. This paper presents decision-making models and advanced algorithms for RFID-enabled vehicle deployment process that parks a finished vehicle into the plant yard before its shipment to a dealer. In addition, it validates that using the active RFID tracking, intelligent deployment algorithms further improve the performance. Conventional vehicle deployment strategies are based on a vehicle’s current location already parked in the yard. In fact, the location of a vehicle changes several times from production release to shipment to a dealer and the yard status may change as well. As the RFID can detect location changes of a vehicle, a new deployment strategy is needed, which can capture this information, in near real-time, to make deployment decision. A market-based control algorithm is developed for capturing the dynamics of the deployment process and in addition, a multiagent computational architecture is developed for processing and coordinating a large amount of real-time information.

The rest of the paper is organized as follows. Section 2 describes vehicle deployment process and its environmental dynamics of a shipment yard of an automotive manufacturer. Section 3 presents current vehicle deployment practice. Section 4 discusses a new operational process for vehicle deployment in which an RFID tracking system is in place, and Section 5 presents a market-based decision-making approach for the new vehicle deployment process. The computational experiments and results analysis are given in Section 6. Finally, the conclusions are drawn in Section 7.

2. Vehicle deployment process

This section details the vehicle deployment process in a shipment yard of an automobile manufacturer by describing the operations and defining an associated performance measures. In order to discuss dynamic characteristics of the vehicle deployment process, the mathematical model for vehicle deployment is presented along with the limitations for applying the model to a real shipment yard environment. At the end of this section, the best available vehicle deployment practice in a current shipment yard environment is presented for the purpose of comparing vehicle deployment performance.

2.1. Description of vehicle deployment operations

Once a vehicle is released from an assembly plant, it stays at a temporary buffer of a shipment yard as shown in Fig. 1. Subsequently, the vehicle moves to a general truck buffer or a general train buffer according to its pre-determined delivery transportation mode. The general buffers store a number of vehicles until they move to loading buffers where they are loaded onto trucks or trains for delivery. In fact, every finished vehicle has its delivery destination, with a corresponding transportation mode, assigned by a delivery schedule. Since train transportation limits delivery destinations, and consequently, the nature of the vehicle deployment process is relatively less dynamic, this study focuses on truck transportation only. Before actual loading onto trucks, the vehicles first move from the general buffer to a truck loading buffer consisting of many loading locations. The truck in each loading location has a particular delivery destination, e.g., Philadelphia, PA.

Vehicle deployment consists of two main operations: (1) yard operators move vehicles from the temporary buffer to available parking slots in the general buffer, and (2) truckers move vehicles from the general buffer to designated loading locations in the loading buffer. For a single vehicle deployment, these two main operations are further divided into four elementary operations. Fig. 2 shows these elementary operations where operations, EO-I and EO-II, are performed by yard operators, and EO-III and EO-IV, are performed by truckers.

| EO-I | Driving vehicle i from vehicle pick up point Q in the temporary buffer to allocated parking slot b_i in the general buffer |
| EO-II | Riding back to the temporary buffer from parking slot b_i. Since the distance between the temporary buffer, located near the assembly plant, and the general buffer located in the shipment yard is quite long, a yard operator comes back to the temporary buffer via a transportation utility like a van |
| EO-III | Walking from loading location L_i for vehicle i in the loading buffer to parking slot b_i to pick up the vehicle i. Since the general buffer and the loading buffer adjoin, a trucker moves from the loading buffer to the general buffer by walking |
| EO-IV | Driving vehicle i from parking slot b_i to its loading area L_i |

2.2. Performance measure for vehicle deployment

A vehicle deployment problem is a problem of allocating one of the available parking slots in the general buffer to a newly produced vehicle by minimizing handling time, i.e., a consolidated operational time, defined as the total time required for the four elementary operations listed earlier.

The consolidated operational time mainly depends on driving, riding, and walking distance matrices between every pair of locations in the shipment yard. However, the matrices cannot be easily generated by hand due to the size of a typical shipment yard which may have more than a thousand parking slots. Because of that, a model may consist of an approximation of driving, riding, and walking distances (i.e., rectilinear distance for driving and riding and Euclidean distance for walking).

Driving and riding distances can be approximately calculated by rectilinear distance because the general buffer is filled with vehicles, and both vehicles and the van can move only along accessible roads in the shipment yard. For example, driving and riding distances between two locations m and n, denoted by $D_d(m,n)$ and $D_r(m,n)$ are calculated by

$$D_d(m,n) = D_r(m,n) = |x^m - x^n| + |y^m - y^n|$$  \hspace{1cm} (1)

where $x^i$ and $y^i$ denote an x-coordinate and a y-coordinate of location $i$, respectively.
Computation of walking distance between two locations \( m \) and \( n \), \( D_{w/m,n} \), uses Euclidian distance:

\[
D_{w/m,n} = \sqrt{(x_m - x_n)^2 + (y_m - y_n)^2}
\]  

Using the approximated distance matrices, operational times for a yard operator and a trucker for deployment of vehicle \( i \) are calculated as

\[
OT_Y(b_i) = \frac{D_d \langle Q, b_i \rangle}{s_d} + t_{wait} + \frac{D_r \langle b_i, Q \rangle}{s_r}
\]  

(3)

\[
OT_T(L_i, b_i) = \frac{D_w \langle L_i, b_i \rangle}{s_w} + \frac{D_d \langle b_i, L_i \rangle}{s_d} + t_{load}
\]  

(4)

where \( s_d, s_r, \) and \( s_w \) are unit speeds for driving, riding, and walking, respectively. In Eq. (3), \( t_{wait} \) denotes the amount of time for a yard operator to wait for a van, and \( t_{load} \) in Eq. (4) denotes the time a trucker uses to load a vehicle onto a truck.

Finally, the consolidated operational time for deployment of vehicle \( i \), \( COT(L_i, b_i) \), is defined as the sum of operational times for both a yard operator and a trucker:

\[
COT(L_i, b_i) = OT_Y(b_i) + OT_T(L_i, b_i) = \left(\frac{D_d \langle Q, b_i \rangle}{s_d} + t_{wait} + \frac{D_r \langle b_i, Q \rangle}{s_r}\right) + \left(\frac{D_w \langle L_i, b_i \rangle}{s_w} + \frac{D_d \langle b_i, L_i \rangle}{s_d} + t_{load}\right)
\]  

(5)

2.3. Dynamic characteristics of vehicle deployment planning

Because of the release of finished vehicles from the assembly plant to the temporary buffer is sequential, over time, the decisions for corresponding parking slot allocations are also made by solving a series of vehicle deployment problems, and each vehicle deployment decision should be made interactively with other vehicle deployment decisions. In other words, a vehicle deployment decision made in the current decision epoch affects later decisions, and in addition, the overall status of the yard could become uncertain, over time, due to changes in vehicle production schedules, truck arrival schedules, and the immediate yard status.
To present a sequence of interrelated vehicle deployment decisions, $f_t(B')$ denotes the minimum value of the total consolidated operational time for the vehicles released, where $B'$ represents the set of available parking slots in the general buffer at time $t$. The recursive relationship for the deployment planning problem, which provides a systematic representation for determining the optimal combination of vehicle deployment decisions, is modeled as

$$f_t(B') = \min_{b \in B'} (COT(t, b_t) + f_{t+1}(B'_{-t-1})), \quad \forall t$$

(6)

where decision epoch $t$ implies the time when the assembly plant releases a newly finished vehicle to the temporary buffer. Since it is assumed that vehicles are released to the temporary buffer one-by-one, an index $t$ can be interpreted as an index for a vehicle. The decision variable $b_t$ is the allocated parking slot for vehicle $t$ and $L_t$ denotes the designated loading location for that vehicle (i.e., the vehicle released to the temporary buffer at time $t$). The dynamics of the set of available parking slots is represented as

$$B^+ = [B \setminus \{b_t\}] \cup \tilde{B}^+_{t-1}, \quad \forall t$$

(7)

where $b_t$ is the parking slot allocated to the vehicle $t$, and $\tilde{B}^+_{t-1}$ is the set of parking slots newly emptied between time $t$ and $t+1$.

In the shipment yard, newly emptied parking slots in the general buffer appear because of the following: (1) a parking slot in the general buffer becomes empty as the vehicle parked in it moves to a loading location for shipment based on shipment load makeup schedules, and (2) vehicles in the general buffer can be put on hold and/or returned to the plant due to unexpected product quality abnormalities. Once a quality problem is reported, quality inspectors hold the vehicles or move them to the plant for investigation and/or corrective action. Those unexpected events affect not only vehicle shipment schedules, but also availability of parking slots in the general buffer.

Furthermore, the vehicle shipment schedule cannot be exactly predicted due to various shipment scheduling environment dynamics, such as changes in delivery orders, delays in truck arrivals, human errors, etc. Owing to these primary reasons, the set of available parking slots continuously changes throughout the planning time horizon. These inherent dynamics in the vehicle deployment environment lead to have an adaptable and flexible decision-making approach that can handle the inevitable dynamics.

3. Current best vehicle deployment practice

This section deals with the current best vehicle deployment practice in response to the dynamic shipment yard environment in the absence of real-time tracking. This deployment practice is the basis line for validating a new vehicle deployment model with an RFID-enabled shipment yard and for analyzing the value of RFID technology.

In the current shipment yard, the status of the available parking slots in the general buffer is periodically updated, perhaps once a day, by a manual reporting process. Yard operators and truckers manually inform a yard manager of the availability of parking slots after moving vehicles from the temporary buffer to the general buffer, or from the general buffer to loading locations. Since this manual reporting and updating process takes a certain amount of time, immediate updating of the availability of parking slots in the general buffer is not possible. Fig. 3 illustrates a vehicle-parking slot allocation for the current best vehicle deployment practice.

At the beginning of a certain time period, the set of available parking slots, $B$, is given for the allocations of vehicles that will be released from the assembly plant to the temporary buffer during this time period. Since accuracy of a vehicle production schedule is unpredictable, the allocation of a vehicle to a parking slot occurs at the actual release of a finished vehicle to the temporary buffer, and each subsequent allocation in this period occurs only on the basis of the set of available parking slots, $B$, provided at the beginning of this period. In other words, even though some parking slots may become empty during this period, this information is not reflected for the decision during this period, due to the nature of manual updating process. By solving problem (8), one of the available parking slots $B$ is assigned to vehicle $i$ that is released during this period in order to minimize the consolidated operational time:

$$\text{Min} \sum_{b \in B} \left\{ \frac{D_d(L, b)}{S_d} + t_{wait} + \frac{D_t(Q, b)}{S_t} \right\} x_b$$

subject to \( \sum_{b \in B'} x_b = 1, \quad B' = B \setminus b, \quad x_b \in (0, 1), \quad \forall b \in B' \) (8)

where binary decision variable $x_b$ is 1 if vehicle $i$ is allocated to parking slot $b$, $b \in B'$, otherwise 0. In this formulation, $B'$, the set of available parking slots for vehicle $i$, is obtained from $B$ by excluding $B''$, $B'' \subset B$, where $B''$ denotes the set of parking slots that are already allocated to the vehicles released to the temporary buffer earlier than vehicle $i$ during this period.

4. Vehicle deployment in RFID-enabled shipment yard

In the RFID-enabled shipment yard shown in Fig. 4, a vehicle has an active RF tag attached before its release to the shipment yard. The attached RF tag transmits real-time information about the vehicle and its location to RFID readers. RFID data server receives all data collected by the RFID readers. The RFID system used in this study is an already proven active tag based RFID system called real-time locating system (RTLS, 2010). The RTLS consists of RFID tags, readers with antennas, processors, and yard management system software. The customized software uses a digital mapping that matches the real yard with a CAD-based geographical map.
When an RF tag attached to a vehicle sends a signal for its location in every 5 s, the signal is received and processed by the readers and the software displayed the x, y coordinates of a vehicle’s location in the yard to the user interface screen. This (near) real-time changing vehicle location information in 5–10 ft accuracy range is used for deployment planning. The software application provides features, such as the history of a vehicle’s location changes with time stamps, the inventory list of vehicles at a certain time point, the number of vehicles in a particular business process, etc. This level of accuracy is good enough for yard operators to physically locate and deploy the vehicle to the yard. Yard operators obtain work orders via wireless devices, such as personal digital assistants (PDAs) or tablet PCs. The work order includes information about the vehicle to be retrieved from the temporary buffer and its assigned parking slot in the general buffer.

The vehicle deployment planner can track currently available parking slots and vehicles waiting for allocation in real-time. To utilize this information obtained from the RFID data server, a new vehicle-parking slot allocation strategy needs to consider the following: (1) the method for utilizing the real-time information about the vehicles and the available parking slots to assign initial parking slots to the vehicles released from the plant and (2) the method for updating the initial vehicle deployment decision to reflect dynamic changes, as the set of available parking slots changes.

### 4.1. Initial decision for vehicle deployment

Whenever a newly produced vehicle is released to the temporary buffer, the yard manager obtains the vehicle’s information, such as its delivery destination and loading location, from a vehicle production information system linked to the vehicle deployment planner through an interface. The RFID tracking system automatically updates the currently available parking slots in real-time, and a parking slot allocation decision for newly produced vehicle i can be made by solving

\[
\begin{align*}
\text{Min} & \frac{b \in B^f \sum_i \left( \frac{D_{b \in B^e} Q_{b \in B^e}}{s_g} + t_{\text{wait}} + \frac{D_{b \in B^v} Q_{b \in B^v}}{s_f} \right) + \left( \frac{D_{b \in B^e} L_{b \in B^e}}{s_g} + \frac{D_{b \in B^v} L_{b \in B^v}}{s_d} + t_{\text{load}} \right) \right) x_i^b \\
\text{subject to} & \sum_i x_i^b \leq 1, \quad B^f = B^e \cup B^v, \quad x_i^b \in \{0, 1\}, \quad \forall b \in B^f
\end{align*}
\]

where a binary decision variable \(x_i^b\) is 1 if parking slot \(b\), \(b \in B^f\), is allocated to vehicle \(i\), otherwise 0. In the above formulation, the set of available parking slots for vehicle \(i\), \(B_i\), is obtained from the RFID system that detects two sets of parking slots, \(B_i^e\) and \(B_i^v\), the set of all empty parking slots upon release of vehicle \(i\) and \(B_i^e\) is the set of empty parking slots allocated to other vehicles currently in the shipment yard but not completely moved into the assigned parking slots.

### 4.2. Updating vehicle deployment decisions

A vehicle released into the temporary buffer requires a certain amount of time until its movement to a parking slot in the general buffer is complete. Two types of operational delays explain this amount of time. One is that a vehicle has to stay in the temporary buffer until a yard operator becomes available to move it, and the other is the time required to move the vehicle from the temporary buffer to an assigned parking slot in the general buffer. As discussed in Section 2.3, the set of available parking slots continuously changes during this time period due to dynamic events. Thus, the initial deployment decisions made in the previous section should be updated in response to those changes that may lead to improvement or deterioration of deployment performance. Huang et al. (2005) emphasize that updating an initial decision should be improved to improve the adaptiveness and competitiveness of decision-making strategies in a dynamic environment.

The RFID tracking system can monitor the real-time availability of parking slots by capturing unexpected events in the shipment yard. Whenever a newly emptied parking slot is detected, the allocated parking slots for the vehicles not completely moved into the parking slots can be changed. The problem of updating currently allocated parking slots is mathematically formulated as

\[
\begin{align*}
\text{Min} & \sum_{i \in V^f} \sum_{b \in B^e} \left( \frac{D_{b \in B^e} Q_{b \in B^e}}{s_g} + t_{\text{wait}} + \frac{D_{b \in B^v} Q_{b \in B^v}}{s_f} \right) \\
& + \left( \frac{D_{b \in B^e} L_{b \in B^e}}{s_g} + \frac{D_{b \in B^v} L_{b \in B^v}}{s_d} + t_{\text{load}} \right) \right) x_i^b \\
\text{subject to} & \sum_{b \in B^f} x_i^b \leq 1, \quad \forall b \in B^f \cup \{b_{\text{new}}\}
\end{align*}
\]

Constraint (11) ensures a vehicle is assigned to at most one vehicle, and Constraint (12) ensures that the initial decision is updated by assigning more vehicles to parking slots in the general buffer yet, \(B^e\) denotes the set of parking slots allocated to the vehicles in \(V^f\), and \(b_{\text{new}}\) is the newly detected empty parking slot in the general buffer. Since the number of vehicles in \(V^f\) is the same as the number of bays in \(B^e\), \(|V^f| = |B^e|\), the problem is formulated as an allocation problem of \(n\) vehicles (jobs) to \(n+1\) parking slots (resources), including \(b_{\text{new}}\). Constraint (11) ensures a parking slot in \(B^f \cup \{b_{\text{new}}\}\) is assigned to at most one vehicle, and
constraint (12) ensures a vehicle in $V_i$ is allocated to only one parking slot from those available slots. Finally a binary decision variable $x_{ij}$ is 1 if parking slot $b_i$ is allocated to vehicle $i$, otherwise 0.

5. Market-based approach for vehicle deployment

The problem of updating vehicle deployment decisions, discussed in Section 4.2, is formulated on the basis of centralized information processing and decision-making in which the vehicle deployment planner should be aware of all deployment related information, such as vehicles’ current locations and loading locations, availability of parking slots, and other dynamic events. Moreover, the above decision problem should be solved repeatedly upon detection of a new empty parking slot. When the number of vehicles in the yard increases a great deal and dynamic uncertainties grow, the centralized decision-making approach may not be adequate for processing a large amount of distributed information and may be unable to provide prompt decisions.

To overcome the limitations of the centralized decision-making approach, this study proposes a multiagent-based decision-making framework in which a market-based control mechanism is facilitated to accommodate the dynamics associated with different participants and to process large amounts of distributed information.

5.1. Design of agents

The essential issue of designing a multiagent-based decision-making framework is to define the individual agent. In this case, the updating process of vehicle deployment decisions requires defining two main agent classes: vehicle agent and yard manager agent. The fundamental roles of these agents and key information they maintain are as follows:

- **Vehicle agent**: A vehicle agent represents an individual vehicle in the shipment yard and is responsible for obtaining an available resource, such as a parking slot in the general buffer. Each vehicle agent maintains vehicle deployment related information, such as current location, loading location, and currently allocated parking slot.
- **Yard manager agent**: The yard manager agent is responsible for managing and coordinating a set of parking slots in the general buffer, and interacts with vehicle agents to update deployment decisions by allocating appropriate parking slots. The yard manager agent can monitor the state of parking slots in the general buffer by accessing the RFID data server.

5.2. Market-based control mechanism

Due to the nature of the updating process of vehicle deployment decisions, discussed in the beginning of Section 5, it is very natural to model the updating process as a negotiation process between competitive participants (vehicles) which need to acquire some resources (parking slots) to achieve their individual goals. An auction is one popular form of market-based control mechanism. For the purpose of handling the process of updating vehicle deployment decisions in the multi-agent decision-making framework, this study designs two different auction mechanisms: an auction heuristic mechanism and an ascending price iterative auction mechanism.

5.2.1. Auction heuristic algorithm

Once a newly emptied parking slot $b_{new}$ is detected, the yard manager agent opens an auction market by sending a request for bid (RFB) message to the vehicles that represent the vehicles in $V_i$, the set of vehicles not completely moved into currently allocated parking slots. The RFB message includes information of parking slot $b_{new}$. In the auction heuristic mechanism, a vehicle agent would update the currently allocated parking slot if a new allocation would provide better utility value. Section 5.3 explains the details of utility value for a vehicle agent.

Let $u_i(b)$ be the utility value of parking slot $b$ for vehicle agent $i$. A vehicle agent, after receiving the RFB message from the yard manager agent, computes the utility value of parking slot $b_{new}$ to determine whether or not the vehicle agent should participate in the auction market. For example, if vehicle agent $i$ can expect better utility by taking $b_{new}$ than by keeping the currently allocated parking slot $b_i$, i.e., $u_i(b_{new}) > u_i(b)$, then vehicle agent $i$ decides to participate in the auction market to obtain $b_{new}$ by submitting a bidding price for $b_{new}$, as defined by

$$p_i(b_{new}) = u_i(b_{new}) - u_i(b)$$

(13)

However, if no vehicle agent can expect the larger or equal utility value by taking $b_{new}$, the market automatically closes.

Once vehicle agents finish submitting their bidding prices for $b_{new}$, the yard manager agent determines a winning vehicle agent $i^*$ that the one who submitted the highest bidding price:

$$i^* = \arg \max_{i \in V} p_i(b_{new})$$

(14)

Now the yard manager agent allocates $b_{new}$ to the winning vehicle agent $i^*$ and consequently opens another market by sending a new RFB message to the remaining vehicle agents in $V_i = V_i \setminus \{i^*\}$. The new RFB message includes information of parking slot $b_{new}$, which is released from vehicle agent $i^*$. The same bidding price submission and winner determination processes continue, as shown in Table 1, and this auction process repeats until no vehicle agent can achieve better utility value from a parking slot broadcasted to vehicle agents by an RFB message, or no vehicle agent in $V_i$ remains.

5.2.2. Ascending price iterative auction algorithm

The fundamental idea of the proposed ascending price iterative auction mechanism is from an $\epsilon$-complementary slackness iterative auction, developed by Bertsekas (1990) to originally solve $n \times n$ allocation problems by matching $n$ jobs to $n$ resources on a one-to-one basis. Since the problem of updating vehicle deployment decisions, formulated in Section 4.2, is an $n \times 1$ parking slots allocation problem, a dummy vehicle agent is added to an auction market to re-design the problem as a one-to-one matching allocation problem.

Once a newly emptied parking slot $b_{new}$ is detected, the yard manager agent calls all the vehicle agents in $V_i$ in order to request information of parking slots currently allocated to vehicle agents. Now, vehicle agent $i$, i.e., $i \in V_i$, responds to the yard manager agent by sending information of its currently allocated parking slot $b_i$. After collecting information of the set of currently allocated parking slots $B_i$, the yard manager agent opens an auction market by sending and RFB message to vehicle agents in $V_i$. The RFB message includes information of the set of all available parking slots including $b_{new}, B_i \setminus \{b_{new}\}$.

In this auction mechanism, it is supposed that parking slot $b$ has a price $p(b)$ and the vehicle agent who takes this parking slot must pay that. Net profit value of parking slot $b$ for vehicle agent $i$ is the difference between the utility value and the price, that is, $u_i(b) - p(b)$. Through the ascending price iterative auction, parking slots are allocated to vehicle agents to maximize the total summation of utility values.
The ascending price iterative auction proceeds in iterations starting with current allocations, where $b_{\text{new}}$ is initially allocated to dummy vehicle agent $v_d$ and initial prices of parking slots are set to zero as shown in Fig. 5.

Each iteration starts with the allocation result and the set of prices taken from the previous iteration, and the iteration continues until all vehicle agents are satisfied with the results of allocation:

$$u_i(b_i) - p(b_i) \geq \max_{b \in B^i \cup \{b_{\text{new}}\}} (u_i(b) - p(b)) - \epsilon$$  \hspace{1cm} (15)

As shown in Eq. (15), vehicle agent $i$ would be satisfied if the net profit value of allocated parking slot $b_i$ is within $\epsilon$ (the minimum price increment) of the maximum net profit value. However, the assumption is that the dummy vehicle agent is always satisfied with any result of allocation through all iterations.

At the beginning of each iteration, if is any vehicle agent $i$ is not satisfied with the previous result of parking slot allocation, this vehicle agent finds parking slot $b_i^*$ that provides the maximum net profit value:

$$b_i^* = \arg \max_{b \in B^i \cup \{b_{\text{new}}\}} (u_i(b) - p(b))$$  \hspace{1cm} (16)

Once vehicle agent $i$ finds the parking slot $b_i^*$, the agent exchanges parking slots with the vehicle agent currently allocated to $b_i^*$ by submitting a new price for parking slot $b_i^*$. If $p_{\text{new}}(b_i^*)$ is the new price for parking slot $b_i^*$, then in this auction market, $p_{\text{new}}(b_i^*)$ is set to the level where vehicle agent $i$ is indifferent between $b_i^*$ and the second best parking slot, as computed by

$$p_{\text{new}}(b_i^*) = p(b_i^*) + (\alpha_i - \beta_i + \epsilon)$$  \hspace{1cm} (17)

where $\alpha_i$ denotes the net profit value of the best parking slot for vehicle agent $i$ and $\beta_i$ represents the net profit value of the second best parking slot. The $\alpha_i$ and $\beta_i$ are computed as

$$\alpha_i = \max_{b \in B^i \cup \{b_{\text{new}}\}} (u_i(b) - p(b))$$

$$\beta_i = \max_{b \notin B^i \cup \{b_{\text{new}}\}} (u_i(b) - p(b))$$  \hspace{1cm} (18)

By the above definition, the price increment (bidding increment) is always at least equal to $\epsilon$.

As described in Table 2, the above process in the ascending price iterative auction mechanism repeats in a sequence of iterations until all vehicle agents are satisfied with the results of parking slot allocation. The strength of the ascending price iterative auction market is in computational efficiency and the optimal property of an $\epsilon$—complementary slackness auction algorithm ( Bertsekas, 1990). When the auction market terminates, an allocation result is in almost equilibrium and the total sum of utility values of the final parking slot allocation is within $(n+1)\epsilon$ of being optimal, where $n$ is the number of vehicle agents in $V^i$.

5.3. Design of utility function for vehicle agent

Design of the utility function of a vehicle agent for a parking slot considers two principal factors in the vehicle deployment operational environment: consolidated operational time and shipment loading schedule. Since a vehicle agent has a preference for the parking slot requiring less consolidated operational time, as defined in Eq. (5), it makes clear to define the utility value of


\[ \text{Fig. 5. Illustration for a design of the ascending price iterative auction where a dummy vehicle agent is included.} \]
Parking slot \( b \) for vehicle agent \( i \), \( u_i(b) \) in Eq. (19), as a reciprocal form of the consolidated operational time for vehicle \( i \) to parking slot \( b \):
\[
u_i(b) = \frac{1}{\text{COT}(L_i,b)}
\]  
(19)

In the shipment yard, vehicles in the general buffer move to designated loading locations based on a predefined shipment loading schedule. In general, the shipment loading schedule primarily considers a vehicle’s delivery priority. For example, a vehicle with a high delivery priority is expected to be shipped earlier than a vehicle with a lower delivery priority. Table 3 describes a simple instance of creating a shipment loading schedule that follows a high-priority-first-loaded (HPFL) rule. As a result of the HPFL-based loading schedule, the amount of time a vehicle with a higher delivery priority stays in a general buffer before moving to a designated loading location is likely to be shorter than the amount of time a vehicle with a lower delivery priority stays.

In order to reduce the overall consolidated operational time during a planning time period, the parking slot that creates lower consolidated operational time should be highly utilized by allocating vehicles to the parking slot, as many as possible, during the planning time period. This goal is achieved by decreasing the amount of time a vehicle stays in this parking slot. For this reason, a vehicle agent with a higher delivery priority has greater utility value of a parking slot than a vehicle agent with a lower delivery priority. Finally the utility value of parking slot \( b \) for vehicle agent \( i \), \( u_i(b) \), is computed by
\[
u_i(b) = (1 + \alpha_o) \left( \frac{\text{COT}(L_i,b)}{C_0} \right)^{-1} = \left(1 + \alpha_o \right) \left\{ \frac{D_q(b,Q)}{S_q} + \frac{t_{\text{wait}}}{S_w} + \frac{D_q(b,Q)}{S_q} + \frac{D_q(b,L_i)}{S_d} \right\}^{-1}
\]  
(20)

where \( \alpha_o \) denotes delivery priority of vehicle \( i \). The value of \( \alpha_o \) is set to within \( 0-1 \). \( 0 < \alpha_o < 1 \), and a larger \( \alpha_o \) implies higher delivery priority.

6. Computational experiments

Computational experiments conducted with simulation validated the new design of the market-based control for the vehicle deployment process in the RFID-enabled shipment yard. This section presents the experimental setup followed by the experimental analysis results.

6.1. Experimental setup

Computational experiments compare four different vehicle deployment models, classified in Table 4, are compared in terms of consolidated operational time, shipment yard utilization, and labor consumption. Vehicle deployment models considered in the experimentation are as follows:

- **CVD**: Current best vehicle deployment practice model, described in Section 3.
- **RVD\textsuperscript{D2}**: RFID-enabled vehicle deployment model with initial deployment decision only, described in Section 4.1.
- **RVD\textsuperscript{D2+AH}**: RFID-enabled vehicle deployment model with updating initial deployment decisions using the auction heuristic, described in Section 5.2.1.
- **RVD\textsuperscript{D2+IA}**: RFID-enabled vehicle deployment model with updating initial deployment decision using the ascending price iterative auction, described in Section 5.2.2.

---

**Table 2**: Algorithm: ascending price iterative auction for updating vehicle deployment decisions.

<table>
<thead>
<tr>
<th>Step</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>STEP 1</strong></td>
<td>Yard manager agent—opening auction market</td>
</tr>
<tr>
<td></td>
<td>DO Request currently allocated parking slot ( b ) to vehicle agent ( i ), for ( \forall i \in V )</td>
</tr>
<tr>
<td></td>
<td>DO Send RFB message including ( b^{\text{old}} ), ( b_{\text{new}} ) to vehicle agents in ( \forall i \in V )</td>
</tr>
<tr>
<td></td>
<td>GO TO STEP 2</td>
</tr>
<tr>
<td><strong>STEP 2</strong></td>
<td>Vehicle agents—submitting bidding price</td>
</tr>
<tr>
<td>FOR Vehicle agent ( i ), ( \forall i \in V )</td>
<td></td>
</tr>
<tr>
<td></td>
<td>IF ( u_i(b_i) - p(b_i) \geq \max { u_i(b) - p(b) } - c ) THEN</td>
</tr>
<tr>
<td></td>
<td>Submit new bidding price ( p_{\text{new}}(b_i) ) for ( b_i )</td>
</tr>
<tr>
<td></td>
<td>ELSE</td>
</tr>
<tr>
<td></td>
<td>DO Nothing</td>
</tr>
<tr>
<td></td>
<td>END IF</td>
</tr>
<tr>
<td></td>
<td>END FOR</td>
</tr>
<tr>
<td><strong>STEP 3</strong></td>
<td>Yard manager agent—terminating auction market</td>
</tr>
<tr>
<td></td>
<td>-&gt; IF ( u_i(b_i) - p(b_i) \geq \max { u_i(b) - p(b) } - c ) for ( \forall i \in V ) THEN</td>
</tr>
<tr>
<td></td>
<td>Load vehicle ( j )</td>
</tr>
<tr>
<td></td>
<td>( v_h = v_h(j) )</td>
</tr>
<tr>
<td></td>
<td>ELSE IF ( j' \mid j' &gt; 1 ) THEN</td>
</tr>
<tr>
<td></td>
<td>Find ( j' \mid j' = \arg \max_o (c_o) )</td>
</tr>
<tr>
<td></td>
<td>Load vehicle ( j' )</td>
</tr>
<tr>
<td></td>
<td>( v_h = v_h(j') )</td>
</tr>
<tr>
<td></td>
<td>END IF</td>
</tr>
<tr>
<td></td>
<td>END FOR</td>
</tr>
</tbody>
</table>

**Table 3**: Instance of a shipment loading schedule that follows a high-priority-first-loaded (HPFL) rule.

**Table 4**: Classification of vehicle deployment models.

<table>
<thead>
<tr>
<th>Description</th>
<th>Vehicle deployment model</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CVD</strong></td>
<td><strong>RVD\textsuperscript{D2}</strong></td>
</tr>
<tr>
<td>RFID tracking system</td>
<td>No</td>
</tr>
<tr>
<td>Initial deployment decision</td>
<td>Yes</td>
</tr>
<tr>
<td>Multiagent-based updating of deployment decision</td>
<td>No</td>
</tr>
<tr>
<td>Market-based control algorithm</td>
<td>Described in Section 3</td>
</tr>
<tr>
<td>Note</td>
<td>-</td>
</tr>
</tbody>
</table>
6.2. Consolidated operational time

It is obvious that the consolidated operational time depends on the vehicle's allocated parking slot in the general buffer. Table 5 shows the experimental results for the average operational times for each elementary operation\(^1\) and the average consolidated operational times for the different vehicle deployment models. The average operational times for the operations EO-I and EO-II, conducted by a yard operator, are slightly increased in RVD\(^{ID}\), RVD\(^{ID+AH}\), and RVD\(^{ID+IA}\), as compared to the operational times in CVD. However, the average operational time for EO-III, the walking operation from a loading location to a parking slot by a trucker, is considerably decreased to 45.03%, 55.67%, and 57.40%, in RVD\(^{ID}\), RVD\(^{ID+AH}\), and RVD\(^{ID+IA}\), respectively. As a result, the average consolidated operational time for a single vehicle is reduced to 20.15% in RVD\(^{ID}\), 25.75% in RVD\(^{ID+AH}\), and 26.84% in RVD\(^{ID+IA}\) when compared to CVD. These results indicate that real-time information on vehicles and the availability of parking slots, provided by the RFID tracking system, creates a significant decrease in a trucker's operational time, which is a dominant factor of the consolidated operational time. This fact is quite reasonable because walking from a loading location to a parking slot is the most time-consuming operation in vehicle deployment.

As shown in the above figures, RFID-enabled vehicle deployment models improve with updating the vehicle deployment decision made by the RFID tracking system. In terms of the average operational time for EO-III, 19.36% and 22.51% are the improvements for RVD\(^{ID+AH}\) and RVD\(^{ID+IA}\), respectively, as compared to RVD\(^{ID}\), and the average consolidated operational time is enhanced to 7.01% and 8.37% for RVD\(^{ID+AH}\) and RVD\(^{ID+IA}\), respectively.

6.3. Shipment yard utilization

As explained in Section 2.1, the operational time for a trucker depends mainly on the distance from a vehicle in the general buffer to its loading location. From this fact, it is clearly noticeable that increasing the utilization of the parking slots near loading locations is important and may result in a reduction of the operational time for a trucker and, consequently, the consolidated operational time. Investigation of the utilization of a parking slot in different vehicle deployment models introduces two different performance measures: a utilization rate of parking slot and a frequency of parking slot utilization.

6.3.1. Utilization rate of parking slot

The utilization rate of a parking slot is defined as the ratio of the time that the parking slot is occupied by the vehicles during the total simulation time period. Let \( UR(b) \) be the utilization rate of parking slot \( b \). From the result of the simulation study, \( UR(b) \) is computed by

\[
UR(b) = \frac{\sum_{\nu} t(v) \cdot (v, b)}{\text{Total simulation time period}}
\]

where \( V \) is the set of total vehicles moved into the general buffer during the simulation time period, and \( t(v) \) denotes the time period vehicle \( v \) has occupied parking slot \( b \).

Fig. 7a-d shows the utilization rates of parking slots in CVD, RVD\(^{ID}\), RVD\(^{ID+AH}\), and RVD\(^{ID+IA}\), respectively. As shown in the above figures, RFID-enabled vehicle deployment models, RVD\(^{ID}\), RVD\(^{ID+AH}\), and RVD\(^{ID+IA}\), significantly increase the utilization rate of parking slots near loading locations as compared to CVD. It is obviously shown in Fig. 8 that vehicle deployments by RVD\(^{ID+AH}\) and RVD\(^{ID+IA}\) considerably enhance the utilization rate of parking slots near loading locations.

6.3.2. Frequency of parking slot utilization

The utilization rate of a parking slot itself does not accurately reflect the utilization of a parking slot. For example, if a certain vehicle occupies the parking slot preferred for other vehicles for a long time period, this increases the utilization rate of the parking slot defined in Eq. (21). However, from the perspective of vehicle deployment, it is desirable that the parking slot preferred for most vehicles is utilized (occupied) by vehicles as much as possible in

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\(^1\) The elementary operations for a yard operator (EO-I and EO-II) and a trucker (EO-III and EO-IV) are described in Section 2.1.
order to achieve a higher vehicle deployment performance. To this end, the frequency of parking slot utilization becomes a complementary performance measure for examining the utilization of a parking slot. The frequency of parking slot utilization is defined as the number of vehicles allocated into the parking slot during the simulation time period. Let \( F(b) \) be the frequency of parking slot \( b \)'s utilization. From the result of the experimentation, \( F(b) \) is computed by

\[
F(b) = \sum_{v \in V} x_v^b
\]

where \( x_v^b \) is 1 if vehicle \( v \) is allocated to parking slot \( b \), otherwise 0.

Fig. 9a–d shows the frequency of parking slot utilization in CVD, RVD\[D\], RVD\[D\]+AH, and RVD\[D\]+IA, respectively.

As shown in the previous figures, RFID-enabled vehicle deployment models, RVD\[D\], RVD\[D\]+AH, and RVD\[D\]+IA, significantly increase the number of vehicles allocated to the parking slots near loading locations. In other words, the parking slots providing high vehicle deployment performance are utilized by a significantly larger number of vehicles compared to CVD. To clarify this result, Fig. 10 shows the average number of vehicles deployed into the parking slots in each parking slot column (50 parking slots in each parking slot column). The average number of vehicles parked near

![Fig. 7. Utilization rates of parking slots in the general buffer: (a) CVD, (b) RVD\[D\], (c) RVD\[D\]+AH, and (d) RVD\[D\]+IA.](image)

![Fig. 8. Average utilization rate of the parking slots in each parking slot column.](image)
loading locations is considerably more in RVDID+AH and RVDID+IA. This suggests that parking slots near loading locations are highly utilized by moving vehicles into these slots as much as possible, resulting in reduction of consolidated operational time. This result also indicates that the RFID-enabled vehicle deployment models provide a yard manager with an opportunity to reduce the size of the general buffer while enhancing the performance of vehicle deployment.

6.4. Labor consumption

From a shipment yard management point of view, a yard manager is often more interested in reducing the labor time for a trucker than that for a yard operator. Loading a vehicle onto a truck requires more advanced skills, and the labor cost per unit time for a trucker is much higher than for a yard operator. Furthermore, the operational time for a trucker directly affects the amount of time a truck spends in the shipment yard to load a set of vehicles. If a truck spends more time than usual, this causes a delay in loading operations for the trucks coming next and, consequently, results in delays in delivery of vehicles.

This section analyzes the average labor consumption of a yard operator and a trucker for deployment of a single vehicle. Labor consumption is defined as the time required for conducting an assigned operation. By adjusting the labor consumption in CVD
outperform the current vehicle deployment model, CVD, with vehicle deployment models, RVD-ID, RVD-ID+AH, and RVD-ID+IA.

7. Conclusions

The simulation results demonstrate that the RFID-enabled vehicle deployment models, RVD-ID, RVD-ID+AH, and RVD-ID+IA, outperform the current vehicle deployment model, CVD, with respect to the selected performance measures. This proves that applying the RFID technology to a current shipment yard can significantly improve the performance of vehicle deployment by (1) reducing the consolidated operational time, (2) increasing shipment yard utilization, and (3) decreasing labor consumption.

Further, the proposed market-based approach, using the multi-agent computational architecture, improves further system performance because this approach can effectively capture and respond to the dynamic changes in the shipment yard environment by incorporating the large amount of real-time distributed vehicle location information.

In real shipment yards, vehicle shipment schedule and truck arrival schedule also can change dynamically. Future study may include studying the impact of these dynamics on vehicle deployment plans to make the vehicle deployment models more robust. Furthermore, in addition to minimization of consolidated operational time, other decision objectives like deployment efficiency related to frequency of parking slot changes can be added to accommodate more dynamics to the vehicle deployment process.

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