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Application of Agent-Based Approaches to Enhance Container Terminal Operations

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APPLICATION OF AGENT-BASED APPROACHES
TO ENHANCE CONTAINER TERMINAL OPERATIONS

by

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Dedication

To my Mother and Father

<center>ABSTRACT</center>

The globalization of trade and subsequent growth of containerization for transporting goods have brought many challenges for container terminals. Increasing demand, capacity constraints, lack of adequate decision making tools, congestion and environmental concerns are some of the major issues faced by container terminals today. Such terminals involve various processes in their operations and effective decision making is imperative in each process to manage scarce resources and improve the terminals' competitiveness. This dissertation consists of research addressing three critical operational decision problems in marine terminal operations involving application of agent-based modeling. The studies address 1) the truck queuing problem at terminal gates, 2) the inter-block yard crane scheduling problem and 3) the storage allocation problem. These problems share common objectives such as minimizing turn time of drayage trucks, reducing congestion and emission, and enhancing productivity of the terminals.

Queuing at marine terminal gates has long been identified as a source of emissions and high drayage costs due to the large number of trucks idling. The first study in this dissertation addresses queuing of trucks at marine terminal gates and presents a novel agent-based framework where the drayage companies can minimize congestion by using the provided real-time gate queuing information. The problem was tackled based on the approach of the El Farol Bar problem from game theory. Our proposed model can be used as a way of managing demand for the marine terminals, assuming that drayage firms will adjust their plans based

on the real-time feedback of congestion. Results from our experiments suggest that the proposed multi-agent framework can produce steadier truck arrivals at terminal gates and therefore significantly less average waiting time.

To facilitate vessel operations, an efficient work schedule for yard cranes is necessary given varying work volumes among yard blocks with different planning periods. The second study investigates an agent-based approach to assign and relocate yard cranes among yard blocks based on the forecasted work volumes. The objective of this study is to reduce the work volume that remains incomplete at the end of a planning period. Several preference functions are offered for yard cranes and blocks which are modeled as agents. These preference functions are designed to find effective schedules for yard cranes. In addition, various rules for the initial assignment of yard cranes to blocks are examined. The analysis demonstrated that the model can effectively and efficiently reduce the percentage of incomplete work volume for any real-world sized problem.

The storage space allocation problem (SSAP) is the assignment of arriving containers to yard blocks in a container terminal. The third study presents a novel approach for solving SSAP. The container terminal is modeled as a network of gates, yard blocks and berths on which export and import containers are considered as bi-directional traffic. Utilizing an ant-based control method the model determines the route for each individual container based on two competing objectives: 1) balance the workload among yard blocks, and 2) minimize the distance traveled by internal trucks between yard blocks and berths. The model exploits the trail laying behavior of ant colonies where ants deposit pheromones as a function of traveled distance and congestion at the blocks. The route of a container (i.e. selection of a yard block) is based on the pheromone distribution on the network. The results from experiments show that the proposed approach is effective in balancing the workload among yard blocks and reducing the distance traveled by internal

transport vehicles during vessel loading and unloading operations.

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CHAPTER 1

INTRODUCTION

The globalization of trade and subsequent growth of containerization for transporting goods in containers have brought many difficulties and challenges in marine terminal operations. Capacity constraints, lack of adequate decision making tools, congestion and environmental concerns are some of the major issues faced by the container terminals today. Increasing containerization has also resulted in increased complexity in planning for terminal managers to provide satisfactory customer service and maintain terminals competitiveness. Various operations research optimization techniques, automated equipment and information technology have become indispensable for efficient management of marine terminal operations and to attain high productivity in container flow with limited resources.

Marine terminal operations involve various logistics processes and deployment of expensive resources. Thus efficient decision making is imperative in each process to obtain optimum results. This dissertation encompasses research addressing three critical decision making processes in marine terminal operations. They address 1) Truck queuing at terminal gates, 2) Inter-block Scheduling of yard cranes and 3) Storage space allocation problem. All of these problems are concerned with resource optimization and they share common objectives such as minimizing turn time of drayage trucks, reducing congestion and emission, and enhancing the productivity of terminals.

1.1 Research Topic I - Truck Queuing at Terminal Gates

Queuing at marine terminal gates has long been identified as a source of emissions and high drayage costs due to the large number of trucks idling. The first study in this dissertation addresses queuing of trucks at marine terminal gates and presents a novel agent-based framework where the drayage companies can minimize congestion by using the provided real-time gate queuing information. The problem has been tackled based on the approach of El Farol Bar problem from game theory. Our proposed model can be used as a means of managing demand for the marine terminals, assuming that drayage firms will adjust their plans based on the real-time feedback of congestion. Results from our experiments suggest that the proposed multi-agent framework can produce more steady truck arrivals at terminal gate and therefore significantly less average waiting time.

Readers are referred to Chapter 3 of this dissertation for more information about this work, which provides an overview of the truck queuing problem and illustrates how the El Farol Bar problem is adapted as a multi-agent solution framework. A review of related studies is included along with formulation and implementation of the proposed model. Experimental designs of test problems and results are presented to demonstrate the effectiveness of the proposed framework.

1.2 Research Topic II - Inter-block Scheduling of Yard Cranes

Most container terminals use yard cranes to transfer containers between the yard and trucks (both external and internal). Given varying work volumes among yard blocks with different planning periods an efficient work schedule for yard cranes is necessary. The second study of this dissertation develops an agent-based approach to assign and relocate yard cranes among yard blocks based on the forecasted work volumes. The objective of this study is to reduce the work volume that remains

incomplete at the end of a planning period. Several preference functions are offered for yard cranes and blocks which are modeled as agents. These preference functions are designed to find effective schedules for yard cranes. In addition, various rules for the initial assignment of yard cranes to blocks are examined. The analysis demonstrates that the model can effectively and efficiently reduce the percentage of incomplete work volume for any real-world sized problem.

Readers are referred to Chapter 4 of this dissertation for more information about this work, which describes the interblock yard crane scheduling problem and illustrates our proposed methodology in detail regarding the assumptions and the steps of analysis. It also provides a review of related studies and a sample example to demonstrate the approach. The test results from the model based on various real-world sized crane deployment problems are included and results show that the model provides excellent solutions in short time for a range of work volume conditions with high variation.

1.3 Research Topic III - Storage Space Allocation in Yard

The storage space allocation problem (SSAP) is the assignment of arriving containers to yard blocks in a container terminal. The third study presents a novel approach for solving SSAP. The container terminal is modeled as a network of gates, yard blocks and berths on which export and import containers are considered as bi-directional traffic. Utilizing an ant-based control method the model determines the route for each individual container based on two competing objectives: 1) balance the workload among yard blocks, and 2) minimize the distance traveled by internal trucks between yard blocks and berths. The model exploits the trail laying behavior of ant colonies where ants deposit pheromones as a function of traveled distance and congestion at the blocks. The route of a container (i.e. selection of a yard block) is based on the pheromone distribution on the network.

The results from experiments show that the proposed approach is effective in balancing the workload among yard blocks and reducing the distance traveled by internal transport vehicles during vessel loading and unloading operations.

Readers are referred to Chapter 5 of this dissertation for more information about this work. It describes the storage space allocation problem and its importance. In addition to a review of related studies, all necessary detail of the ant-based control method is presented. Then the model implementation steps are illustrated with experimental designs. Finally, the relevant results and the contributions from this research are included. Simulation results show that the proposed approach effectively balances the workload among yard blocks and thus minimizes congestion on the road network for trucks and yard cranes. At the same time, the transport distance of containers between yard blocks and berth is minimized.

1.4   List of Papers and Structure of Dissertation

This dissertation includes three research projects completed and published in peer-reviewed journals and these journal articles appear in the dissertation as separate chapters. They are-

1. Sharif, O., N. Huynh and J. M. Vidal (2011). Application of El Farol Model for Managing Marine Terminal Gate Congestion. *Research in Transportation Economics*, 32(1), 81-89.

2. Sharif, O., N. Huynh, M. Chowdhury, and J.M. Vidal (2012). An Agent-Based Solution Framework for Inter-Block Yard Crane Scheduling Problems. *International Journal of Transportation Science and Technology*, 1(2), 109-130.

3. Sharif, O. and N. Huynh (2013). Storage Space Allocation at Marine Container Terminals Using Ant-Based Control. *Expert Systems with Applications*, 40(6), 2323-2330.

The format of this dissertation follows a manuscript style and the remaining chapters are organized as follows. Chapter 2 provides a brief overview of port operations and highlights related studies. Chapters 3, 4 and 5 include three original research articles mentioned above that have been published in refereed journals. The author of this dissertation is the 'first author' of each article. Chapter 6 concludes this dissertation.

CHAPTER 2

BACKGROUND AND LITERATURE REVIEW

This chapter aims to provide a broad overview of marine terminal and its operations. The chapter also presents a selection of related studies. A comprehensive review of literature on the two completed studies that are included in this dissertation can be found in the respective journal article chapters.

A marine terminal serves as an interface between land and sea where freight/goods are loaded or unloaded to/from ships. The terminal also acts as a buffer for temporarily storing containers before they are picked up by a land truck or loaded on a ship. The cargo ships that moor at a marine container terminal generally fall into two categories- 'container ships' and 'bulk carriers'. A bulk carrier is specially designed to transport unpackaged bulk cargo, such as grains, coal, ore, and cement in its cargo holds. On the other hand, container ships carry their entire load in truck-size intermodal containers, in a technique called 'containerization'. In this research we focus on the latter type i.e. transshipment of cargo using containers. Containers are reusable, large storage boxes used for transporting products and raw materials between locations and 'containerization' is a system of commercial intermodal freight transport using containers. Compared to conventional bulk, the use of containers has several advantages, namely less product packaging, less damaging and higher productivity (Agerschou, 2004). A standard-sized container that is 20 feet long is known as twenty-feet-equivalent-unit (TEU). The capacity of
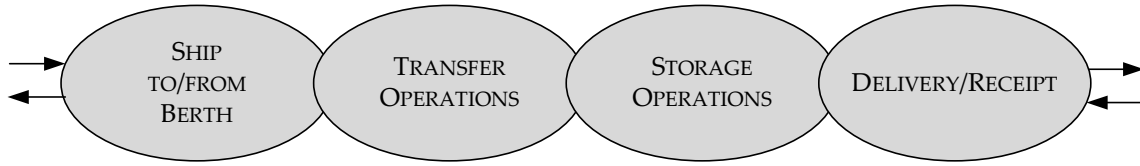
Figure 2.1 Container terminal subsystems (Modified from Henesey (2006))

container ships and container terminals are often expressed in TEUs. According to Zhang et al. (2002), the main functions of container terminals are delivering containers to consignees and receiving containers from shippers, loading containers onto and unloading containers from vessels and storing containers temporarily to account either for efficiency of the deployed equipment or for the difference in arrival times of the sea and land carriers.

Marine container terminals operate under several performance goals but the primary objective is to achieve rapid flow of containers at a minimum cost. In this context, the time to load/unload a ship (the time spent by a ship at berth, also known as 'turn time') has been generally regarded as a measure of container terminal efficiency. Therefore, much research has been focused on the 'marine side' interface of a container terminal, which leaves room for further research such as the 'land side' interface (Henesey, 2006).

2.1 Flow of Containers in a Marine Terminal

The flow of containers in a marine terminal can be viewed as being composed of four broad subsystems. Each container, whether an *import* container or an *export* container, goes through these subsystems between the ship and designated customer/consignee located on land. These subsystems are shown in Figure 2.1.

'Ship to/from berth' is the unloading/loading movement between vessel and berth. 'Transfer' is the movement of containers between berth and container storage area. The 'storage area' is where containers are temporarily stacked. 'Delivery

and Receipt' indicates that a container is delivered to the port by a customer for export or an import container is picked up by a consignee from the port. The two directional arrows in Figure 2.1 indicate that the direction of flow of import and export containers is reverse to one another. Each of these subsystems has a container handling capacity based on their operational strategy and resources deployed. The subsystems all together determine the performance of the container terminal. A bottleneck in any of these subsystems will increase containers transfer time and consequently impact the productivity of terminal and customer service. Also, the interaction and coordination among the four components are critical for the overall performance. However, to date most of container terminal research has focused on the subsystems individually with very few on the whole system or from a 'holistic' view (Henesey, 2006).

The decision types to be made by container terminal managers in each subsystem can be classified into 'planning' decisions and 'controlling' decisions. Henesey (2006) provides an overview what these decisions making processes generally entail. According to his study, planning decision is more concerned with design, development of processes that must be carried out in achieving an efficiently managed terminal and to ensure that the subsystems function in a coherent manner. Control decision is more directed to monitoring and controlling the process and ensuring that levels of productivity are kept within the policy of decisions made by terminal management. As Rushton et al. (2010) put it, planning decision is 'doing the right thing' and control decision is 'doing the thing right.' Furthermore, decision types can be classified into three levels based on the time frame for planning namely 'strategic' level (long term), 'tactical' level (medium term) and 'operational' level (short term). Planning decisions are oriented with strategic level decisions and controlling decisions are oriented with operational level decision. The tactical level decisions embrace both planning and controlling decisions characteristics.

XTs: External Trucks
YCs: Yard Cranes
AGVs: Automated Guided Vehicles
ITs: Internal Trucks
SCs: Straddle Carriers
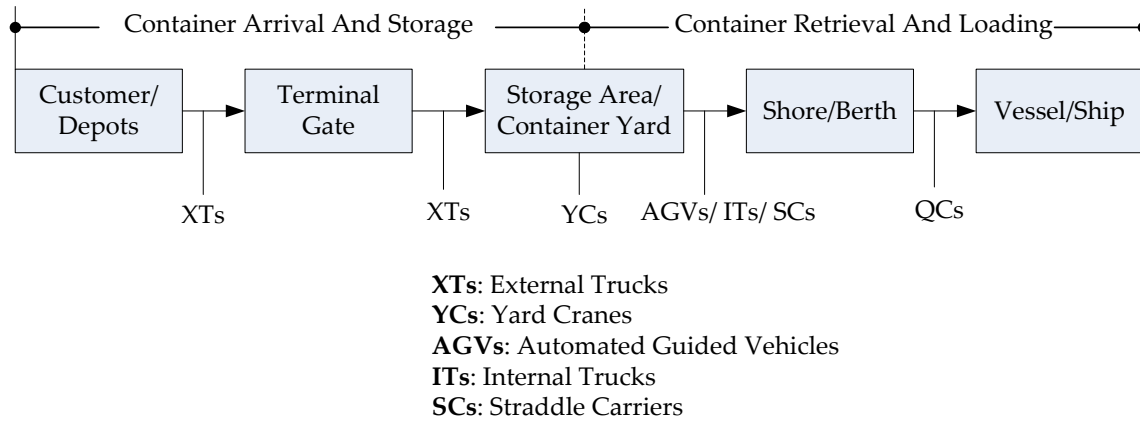
Figure 2.2   Flow of outbound/export containers (Modified from Rashidi and Tsang (2006))

Rushton et al. (2010) and Henesey (2006) present some typical issues addressed in each level of decisions. Strategic level typically involves choice of a terminal location, terminal size, resource types etc. Tactical level typically involves allocation of resources, determining size of workforce etc. Operational level typically involves daily scheduling of jobs, equipments, process management, scheduling of workers, etc.

Since marine terminals serve as an intermodal service for transferring containers between ocean and land, their primary purposes are 1) to receive outbound containers from customers for loading into vessels and 2) to unload inbound containers from vessels for picking up by consignees (Rashidi and Tsang, 2006). These operations are known as export and import processes respectively and the containers are identified as import container (or inbound container) and export container (outbound container). The flows of outbound and inbound containers are illustrated in Figure 2.2 and Figure 2.3. Also, a three dimensional representation of container terminal is shown in Figure 2.4.

To manage the flow of containers, the container terminal employs several specialized and expensive equipments/vehicles for handling and transferring con-
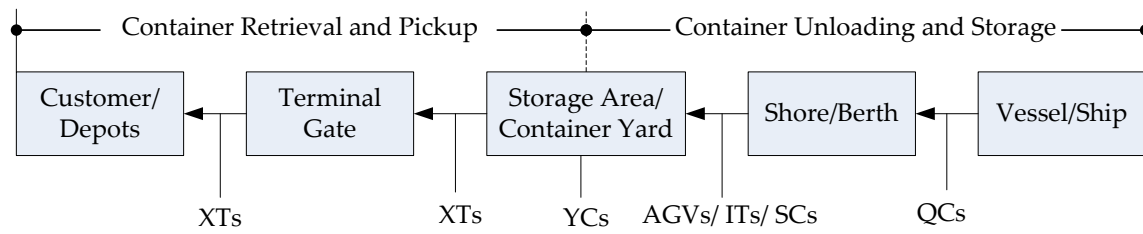
Figure 2.3   Flow of inbound/import containers (Modified from Rashidi and Tsang (2006))
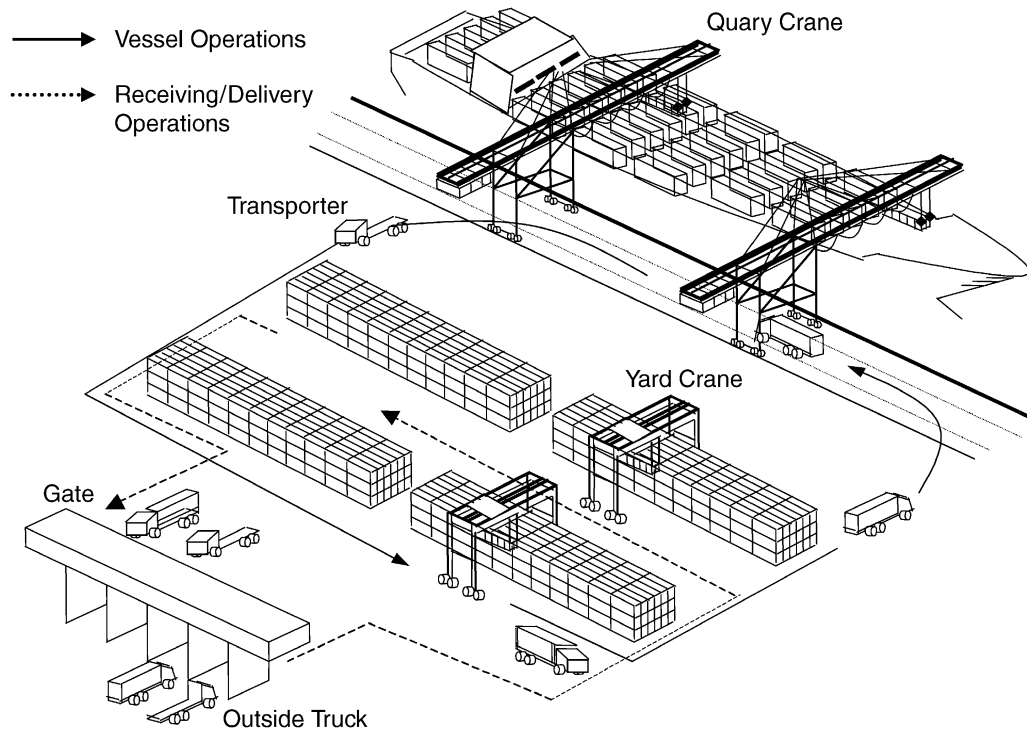
Figure 2.4   A simplified three dimensional view of container terminal

tainers. However since the operational strategy varies among container terminals the choice of equipments deployed may also vary accordingly. The role of these of equipments in various processes within a container terminal will be briefly illustrated in Section 2.2.

2.2 Processes in Container Terminals

It has been mentioned that container terminal operations can be viewed as composed of several processes or subsystems. In this section the operations involved in different subsystems are described in more detail. The various scheduling decisions that need to be made and the equipments that are commonly deployed for container terminal operations are presented. For interested readers, references of some related literature from each process are also included. A comprehensive survey of literature on container terminal operations can be found in several sources e.g. Vis and de Koster (2003), Steenken et al. (2004), Stahlbock and VoB (2008), Crainic and Kim (2007), Murty et al. (2005), Rashidi and Tsang (2006), Vacca et al. (2007), Henesey (2006). However, it should be noted that different authors has used different classification of decisions and processes in a container terminal. For instance, Vis and de Koster (2003) suggested four subclasses of decision problems namely- arrival of a ship, unloading and loading of ship, transport of containers from ship to stack and stacking of containers. Steenken et al. (2004) classified the logistic processes into the ship planning process, storage and stacking logistics and transport optimization. Murty et al. (2005) classified operations into nine decisions namely- allocation of berth to vessels, allocation of QCs, appointment time to external trucks, routing of trucks, dispatch policy at the terminal gate and dock, storage space assignment, RTGC deployment, IT allocation to QC and IT hiring plans. The classification used by Henesey (2006) is as shown in Figure 2.1 and he reviewed literature at strategic, tactical and operational levels in each subprocess. Vacca

et al. (2007) used five types of decision problems which are berth allocation, quay crane scheduling, yard operations, transfer operation and ship stowage planning. The different classification proposed by different authors originate from how they prefer to view or classify port operations. This dissertation assumed six subclasses of decision problems in container terminal and each of them are reviewed briefly in following sections.

Berth allocation

Following the arrival of a ship at port, it must be allocated a place at the quay where it can moor. The places where ships can moor are known as berths. The problem of berth allocation involves assigning a berth to an arriving ship such that the allocation maximizes utilization of berths. Some of the issues that are considered in berth allocation include length of ship, depth of berth, ship's timing window, priorities and berthing preferences, location of berth with respect to stacking area where containers for a particular ship are stored etc. While berth allocation is a decision made at operational level, how many berths should be available at the quay is a part of decision making at strategic level. Berths are critical resources in that they directly relates to capacity of the terminal. Also, the construction of berths entails very high cost relative to the investment made in the other facilities in the port (Park and Kim, 2003).

There are several studies available in literature addressing berth allocation problem at a marine terminal. Rebollo et al. (2000) proposed a multi-agent system architecture to solve the automatic container allocation problem at a terminal so that the berthing time of a vessel can be minimized. Their work is based on the management of container terminal in an actual port. Moon (2000) studied the berth planning problem to determine optimal berthing times and positions of vessels at the terminal. A mixed integer linear programming model was formulated and

a heuristic procedure was suggested for searching a near optimal solution. The static and dynamic berth allocation is studied by Hansen and Oguz (2003) where the objective is to minimize the sum of waiting time of ship and handling time of cargo. In the static case, ships are assumed to arrive before the berths become available; in the dynamic case they can arrive before or after. Imai et al. (2005) presented a heuristic for berth allocation using continuous locations as opposed to discrete locations. In discrete locations scheme, scheduling is relatively easy to address, however, terminal usage is less efficient. In continuous locations case, berth allocation is more flexible especially at busy ports where ships of various sizes moor. Cordeau et al. (2005) studied both discrete and continuous version of berth allocation. They presented two formulations and a tabu search heuristic for the discrete case. A heuristic was also developed for the continuous case. Moorthy and Teo (2006) analyzed the problem of preferred berthing location (home berth) to a set of arriving vessels. They considered the economic impact of the home berth design on the container terminal operations. They model home berth problem as a rectangle packing problem on a cylinder and use a sequence pair based simulated annealing algorithm to solve the problem. Imai et al. (2007) considered indented berths for efficient handling of mega containerships at a container terminal and used genetic algorithms to solve the berth allocation problem. Imai et al. (2008) studied berth and quay crane allocation problem simultaneously. They used genetic algorithm to develop a heuristic to find an approximate solution to the problem. Wang and Lim (2007) proposed a stochastic beam search algorithm to optimize berth allocation. Real data from Port of Singapore was used to evaluate the performance of their algorithm and results indicate that better efficiency can be obtained compared to state-of-art meta-heuristics. Monaco and Sammarra (2007) formulated the discrete berth allocation problem as a dynamic scheduling problem and developed a Lagrangean heuristic algorithm to solve the problem.

Quay crane scheduling

After a ship is docked at a berth, unloading and loading of containers will begin. For this purpose, a number of Quay Cranes (QCs) is assigned to a ship. QCs unload the import containers from ship's deck to shore. The QCs will place the containers to transfer vehicles which travel between the QCs and container stacking area. For export containers, QCs will load them on the ship from the transfer vehicles. Figure 2.5 shows typical QCs deployed at container terminal. Quay Crane scheduling problems involve determining how many QCs will be assigned to a ship and the set of jobs (loading and unloading moves) that will be performed by a QC. Most often the objective of QC scheduling problem is to minimize the time required to unload and load a ship, thereby minimizing ship's turnaround time. The constraints considered are interference between the QCs, precedence relationships among the containers etc. In general, sequence of unloading operations of containers offers more flexibility compared to loading operations since a good distribution of containers over the ship is necessary. A desired distribution of containers is accomplished by 'stowage planning' which is the problem of allocating space to outbound containers on the board of a ship. Stowage planning is influenced by size/type/weight of containers, the ports the ship will be visiting etc. It should be noted that berth allocation and QC scheduling are sometimes considered simultaneously since the berthing time of a ship is in turn dependent of efficient schedules of QCs.

Some of the studies available on quay crane scheduling and ship stowage planning are discussed here. Shields (1984) studied the planning of efficient physical distribution of containers on the board of a vessel. The solution algorithm employed a combination of simulation and Monte Carlo technique. Daganzo (1989) addressed static quay crane scheduling problem where only one crane can

Figure 2.5 Quay cranes working on a container vessel

work on hold of a ship at a time and the objective is to minimize ship's aggregate cost of delay. Exact and approximate solution techniques are developed to solve the scheduling problem. Bose et al. (2000) proposed evolutionary algorithms to optimize the productivity of cranes. Wilson and Roach (2000) studied container stowage problem using automatic generation of computerized solutions that consists of a two stage process using heuristic rules. Lim et al. (2004) examined quay crane scheduling problem with spatial and separation constraints for the first time. Their objective is to find a crane-to-job matching which maximizes throughput under these constraints. The authors provide dynamic programming algorithms, a probabilistic tabu search and squeaky wheel optimization heuristic for solution. Kim and Park (2004) proposed a mixed integer programming model considering various constraints related to quay crane operations. A branch and bound method

is introduced to solve for optimal solution. To overcome computational difficulty of the branch and bound method a heuristic search algorithm was also developed. Moccia et al. (2006) developed a branch-and-cut algorithm for large sized scheduling problems as to minimize the vessel completion time as well as the crane idle times. Sammarra et al. (2007) decomposed the quay scheduling problem into two parts- routing problem and scheduling problem. The routing problem is solved by tabu search heuristic and a local search technique is used to generate the solution of the scheduling problem.

Transport of containers to stack and vice versa

Inbound containers are transported from quay side to storage area and outbound containers are transported from storage area to quay side. The equipments/vehicles that generally perform the transfer operations are Internal Trucks (ITs), Straddle Carriers (SCs), Automated Guided Vehicles (AGVs) and Trucks with multi-trailers. The type of handling equipment that will be deployed for transport operations are strategic level decisions considered when designing a new terminal. SCs are able to lift containers by themselves from the storage yard without assistance of cranes. Thus SCs not only serve as transfer vehicles but also capable of stacking of containers. Because of their lifting abilities they are also known as Automated Lifting Vehicles (ALVs). Figure 2.6 shows a typical SC. AGVs and ITs do not have lifting abilities when compared to SCs. AGVs are unmanned vehicles usually deployed at automated container terminals with the ability of traveling along a predefined route. They are software controlled smart vehicles capable of avoiding obstacles, accelerating/decelerating, as well as overtaking other AGVs. Though they offer high mobility and lower labor cost, high initial capital investment is a concern. In ports with low labor costs, the system of manned vehicles is preferable (Vis and de Koster, 2003). Figure 2.7

Figure 2.6   A straddle carrier

shows a typical AGV. Once what type of equipment will be used for transport is made at strategic level, how many of these equipments is necessary is decided at the tactical level. At the operational level, scheduling and routing of containers are addressed i.e. which container will be handled by which equipment and which path is chosen. Transport operations are usually optimized to minimize number of vehicles, idling of cranes and vehicles, distance traveled by vehicles etc. Some researchers tackled scheduling problem along with storage space allocation of a container (location of a container in yard) as an integrated process. Storage space allocation problem is reviewed in the next section.

A review of related studies on this topic is presented here. Meer (2000) studied the control of guided vehicles in container terminal and examined various dispatching rules under different environments. Bish et al. (2001) addressed the problem of dispatching vehicles in combination with space allocation for con-

Figure 2.7   An automated guided vehicle

tainers in storage area. The objective is to optimize vehicle scheduling such that the total time to unload all containers from the ship is minimized. It is shown to be a NP hard problem and thus a heuristic method is proposed to solve the problem. Huang and Hsu (2002) proposed two integer programs to optimize the dispatching decisions of vehicles. Two heuristic algorithms and Lagrangean relaxation is applied to solve the models. Grunow et al. (2004) studied dispatching of AGVs especially multi-load vehicles which can carry more than one container at a time. A flexible priority rule based approach is developed and mixed integer program is formulated for evaluation purposes and then tested for different scenarios with respect to total lateness of the AGVs. Kim and Bae (2004) examined two different dispatching strategies for AGVs- pooled dispatching and dedicated dispatching. In pooled dispatching an AGV can perform delivery task for multiple QCs, whereas in dedicated dispatching an AGV can perform delivery task for one QC. The study discussed how to dispatch AGVs by utilizing information about locations and times of future delivery tasks. A mixed-integer programming model and heuristic procedure is provided for assigning optimal delivery tasks to AGVs. Liu et al. (2004) developed simulation models to show the effect of automation

and terminal layout on terminal performance. Two terminals with different but commonly used yard configurations are considered for automation using AGVS. A multi attribute decision making method is used to investigate the performance of the two terminals and determine the optimal number of deployed AGVs. Vis et al. (2005) proposed to introduce buffer areas at both quay side and yard side for decoupling of the unloading and transportation processes. The objective is to minimize the vehicle fleet size such that the buffer areas do not exceed their capacity. An integer linear program was developed and simulation was used to verify the analytical results. Cheng et al. (2005) proposed a network flow model taking into account the impact of congestion. The objective is to find a suitable number of AGVs to be deployed and minimize their idling time at berth.

Yard operations - Storage space assignment

Yard operations involves two classes of problems namely storage space assignment and scheduling of yard equipments such as yard cranes. In this section storage space assignment problem (to determine a place for storage or containers) is presented. Yard is an area in the terminal where inbound and outbound containers are temporarily stored before it gets picked up by a truck or stowed onto a vessel respectively. Two types of storage operations can be distinguished - 'wheeled' operations or 'stacking' operations. At 'wheeled terminals' each container is stored on a separate chassis which provides individual accessibility to each container. Since wheeled terminals require plenty of storage space, this option is suitable when land is cheap. At stacked terminals, the containers are stacked on ground and piled on top of one another. This option is suitable for storing more containers in a limited space, however, every container is not directly accessible. Efficient stacking rules are necessary in such terminals to minimize reshuffling and rehandling of containers. Figure 2.8 shows a typical container yard. The container yard generally

Figure 2.8   Container storage area

consists of several rectangular storage blocks known as yard blocks. A typical yard block is 40 forty-foot *bays/slots* long. Each bay is 6 *rows* wide, and containers can be stacked up to 4 *tiers*. Tiers refer to the height to which containers are stacked. The objective of storage space assignment is to determine an optimum space allocation such that handling and rehandling of containers is kept at minimum and traveling time of vehicles is minimized. Thus some researchers have tackled the storage assignment problem along with transportation planning problem.

Chen (1999) described various storage strategies that can lead to high utilization of land in a terminal. Holguín-Veras and Jara-Díaz (1999) addressed the problem of optimal space allocation. Chen et al. (2000) developed a time-space network to assign storage location for containers in advance. A mathematical programming model is proposed to minimize total cost of operation and solved using branch and bound algorithm. Ambrosino et al. (2002) studied the effect of yard organization

in connection with unproductive moves of outbound containers. A binary linear program and a heuristic approach are developed. Zhang et al. (2003) decomposed the storage space allocation problem into two levels and each level is formulated as a mathematical programming model. At the first level, the total number of containers to be placed in each storage block is set to balance workloads among blocks. The second level determines the number of containers associated with each vessel that constitutes the total number of containers in each block in each period. The objective is to minimize the total distance to transport the containers between their storage blocks and the vessel berthing locations. Kang et al. (2006) proposed a method based on a simulated annealing search to derive a good stacking strategy for containers with uncertain weight information. Simulation experiments are used to show that the strategies effectively reduce the number of rehandlings. Lee et al. (2007) studied the storage allocation problem to efficiently transport containers between the vessels and the storage area so that reshuffling and traffic congestion is minimized. To reduce reshuffling, unloaded containers are grouped according to their destination vessel. To reduce traffic congestion, a workload balancing protocol is proposed. Two heuristics are also developed- the first is a sequential method while the second is a column generation method. Lee and Hsu (2007) proposed an optimization model for the container pre-marshalling problem. To minimize the reshuffling, the authors attempted to pre-marshall the containers in such a way that it fits the loading sequence of containers on a vessel.

Yard operations - Yard crane scheduling

It has been recognized that efficiency in yard operations are critical for the overall productivity of the terminal. The efficiency and quality of management is the container yard operations affect all terminal decisions, related to the allocation of available handling equipment and the scheduling of all activities (Rashidi and

Tsang, 2006). In previous section, we reviewed container storage space assignment problem and this section will briefly discuss the scheduling of equipments that are deployed for container storage and retrieval operations. The equipments are used for loading, unloading, rehandling/reshuffling of containers. Choice of equipments for handling of containers is a decision that is made at strategic level. For this purpose forklift trucks, reach stackers, yard cranes are available options. Commonly used yard cranes are Rail Mounted Gantry Cranes (RMGCs) and Rubber Tired Gantry Cranes (RTGCs). Straddle Carriers (SCs) are also a feasible choice and they are reviewed in Section 2.2. RMGCs are also known as Automated Stacking Cranes (ASCs) and they move on rails and can provide high density storage. However, RMGCs can only travel in one direction across the stacks. An RMGC is shown in Figure 2.10. RTGCs, in contrast, are rubber tired and offer more flexibility. RTGCs are popular and more frequently used in large terminals with high container flows and other automated technologies (Henesey, 2006). A typical RTGC is shown in Figure 2.9. The objective of crane scheduling is to maximize utilization of cranes and minimize the waiting time of transport vehicles (ITs, XTs, AGVs etc). The workload at different blocks within a yard changes over time and scheduling must ensure that more cranes are deployed at blocks with heavier workloads. The typical constraints in a scheduling problem are traffic congestion and interference among cranes.

In Zhang et al. (2002) addressed the dynamic crane deployment problem where given the forecasted workload of yard blocks in each period of a day, the objective is to find the times and routes of crane movements among yard blocks so that the total delayed workload in the yard is minimized. A mixed integer program (MIP) was developed and solved using Lagrangean relaxation. Inter-block crane deployment has also been studied by Cheung et al. (2002), Linn et al. (2003) and He et al. (2010). However, these studies do not stipulate detailed work flow for the

Figure 2.9   Rubber tired yard cranes

Figure 2.10   Rail-mounted yard crane

cranes in serving the trucks. Kim et al. (2003) studied various truck serving rules using simulation to minimize truck delay. The sequencing rules comprise dynamic programming, first-come-first-served, unidirectional travel, nearest-truck-first-served, shortest-processing time rule, and a rule set from reinforcement learning. Ng and Mak (2005) studied the problem of scheduling a yard crane to handle a given set of jobs with different ready times. They proposed a branch and bound algorithm to solve an MIP that finds an optimal schedule that minimizes the sum of truck waiting times. In a follow-up study by Ng (2005), the author extended his previous work to deal with multiple yard cranes instead of a single yard crane. His model accounted for interference among cranes which may occur when they are sharing a single bi-directional traveling lane. An integer program was proposed and a heuristic was developed to solve the model. Although this work focused on the yard crane scheduling problem to expedite vessel operations, the proposed model and solution methodology are applicable to drayage operations. In contrast to inter-block deployment studies the study provides detail schedule for handling of individual containers. Lee et al. (2007) studied the scheduling of a two yard crane system which serves the loading operations of one quay crane at two different container blocks, so as to minimize the total loading time at stack area. A simulated annealing algorithm was developed to solve the proposed mathematical model. Li et al. (2009) developed a crane scheduling model where operational constraints such as fixed yard crane separation distances and simultaneous container storage/retrievals are considered. The model was solved using heuristics and a rolling-horizon algorithm. Huynh and Vidal (2010) introduced an agent-based approach to schedule yard cranes with a specific focus on assessing the impact of different crane service strategies on drayage operations. In their work, they modeled the cranes as utility maximizing agents and developed a set of utility functions to determine the order in which individual containers are

handled.

Delivery and receipt operations

Export containers are brought into the port and import containers are picked up from the port by external trucks (XTs). For both delivery and receipt operations, external trucks (also known as drayage trucks) have to pass through terminal gates for documentation processing, inspection, security checks etc. The objective of optimizing delivery and receipt operations is to minimize the turn time of drayage trucks. The turn time of drayage trucks primarily consists of two components-waiting at gate and waiting at yard. Figure 2.11 shows trucks wating at a terminal gate. Idling at yard implies waiting for a yard equipment to come to the truck and load/unload the container to/from the truck. Also, long queue of trucks at terminal gates is a concern since it leads to larger turn time and emission due to congestion. In recent years, some ports have adopted appointment/reservations systems to reduce queuing at gates, where truckers select from a given list of available time windows to arrive to pickup or deliver their containers. However, studies indicate that current appointment strategies have not improved the queuing situation. Because of the lack of specific guidelines for implementing the appointment systems and that each terminal is left to manage their own system, the lack of structures in the appointment system has led to little time savings for truckers as reported in the work of Giuliano and O'Brien (2007). Another approach being experimented by some terminals is to provide live views of their gates via webcams. However, no guidelines or studies are available how to utilize this information to the benefit of truck dispatchers.

Limited research has been focused in the delivery and receipt operations compared to the other processes in a terminal (Henesey, 2006). These works are addressed from either the drayage operator's or terminal operator's perspective.

Figure 2.11   Trucks waiting at a container terminal gate

Huynh and Walton (2008) determined the maximum number of trucks a terminal operator could allow into its terminal based on available resources and investigated the effect of limiting the truck arrivals on the terminal's throughput and resource utilization. In a related study, Huynh (2009) explored rules for scheduling trucks to minimize total delays to trucks. Guan and Liu (2009) utilized a multi-server queuing model to analyze marine terminal gate congestion and quantified truck waiting cost. In the same study, they proposed an optimization model to balance the gate operating cost and truckers' cost due to excessive waiting time.

Unlike terminal operators who dictate how a terminal is run, the drayage operators are users who must follow the policies set by the terminal operators. Given their constraints, the drayage operators' primary aim is to avoid idling time at the terminals. They can accomplish this by scheduling their fleet to meet the appointment windows or avoid congestion periods. Work in this area include a study by Namboothiri and Erera (2008) who examined how a port's appointment-based access control system affects the management of a fleet of trucks providing container pickup and delivery service to a port. Similarly, Ioannou et al. (2005) investigated methodologies for the generation of optimum or near optimum time

windows for cargo delivery/pickup at marine container terminals taking into account the objectives and constraints of the terminal operator and freight carriers.

2.3 RESEARCH TRENDS IN CONTAINER TERMINALS

There is a large amount of literature in the area of marine container terminal modeling. As the container terminal operations are becoming more and more important, the numbers of publications appearing in literature are also increasing. In most instances, operation research optimization methods such as mathematical programs and meta-heuristics are employed by researchers to tackle the container terminal decision problems. Research papers on container terminals can be distinguished in three classes: a) an intensive study or sophisticated model of a single process or decision problem, b) two or more related decision problems as an integrated process or model c) model of an entire container terminal as a coordinated system of container flow. To date, the approach of independent decision problems is most common where a particular operation is optimized rather than integrating several processes or optimizing the whole system. However, more efficiency can be achieved when related processes in terminal operations are considered together. The few studies available in literature adopting integrative views applied analytical, simulation and multi-agent approaches.

2.4 CONTRIBUTION TO LITERATURE

As mentioned previously in Chapter 1, this dissertation incorporates significant research conducted in three critical processes of marine terminal operations. They are the truck queuing problem at terminal gates, the interblock yard crane deployment and the storage space allocation problem. All of these problems are concerned with resource optimization and they share common objectives such as minimizing turn time of drayage trucks, reducing congestion and emission,

and enhancing the productivity of terminals. The research carried out in this dissertation contribute to the container terminal literature on both land and water side interface operations. Much research has been focused on the marine side interface of a container terminal, however, the land side interface has not received adequate attention until recently as the environmental issues and high drayage cost have become major concerns. Also, the contribution of the dissertation is important in that all of the papers involve investigation of applicability of agent-based approaches. Agent-based modeling is a new paradigm being introduced to container terminal operations. More specific contribution to literature made by the three research papers are briefly discussed in the following sections.

Study on 'Truck queuing at terminal gates'

The contributions of this study to literature are: 1) it is the first study to analyze the potential benefits or adverse effects of providing real-time gate congestion information, 2) it examines ways in which the dispatchers and truckers could take advantage of the provided real-time information such that their collective truck queuing time is minimal, and 3) it presents an agent-based framework to be used by truck dispatchers to achieve steady arrival of trucks and hence less queuing at terminal gates.

Study on 'Inter-block yard crane deployment'

The contributions of this study to the literature are: 1) It provides an agent based framework for solving the inter-block crane deployment problem, 2) It presents an approach that effectively minimizes the percentage of incomplete work volume, 3)it is a scalable and time efficient approach, and 4) it offers various strategies of initial assignment of yard cranes.

Study on 'Storage space allocation problem'

The contributions of this study to the literature are: 1) It provides an agent-based framework for solving the SSAP, including suitable parameters, 2) It offers an approach that effectively and synchronously minimizes the workload imbalance and container transport distance, 3) it is a relatively simple but adaptive framework that solves the SSAP in real-time, and 4) it is an approach which is uninfluenced by inaccurate/uncertain container arrival information.

APPLICATION OF EL FAROL MODEL FOR MANAGING
MARINE TERMINAL GATE CONGESTION[1]

ABSTRACT

Truck queuing at marine terminal gates has long been recognized as a source of emissions problem due to the large number of trucks idling. For this reason, there is a great deal of interest among the different stakeholders to lessen the severity of the problem. An approach being experimented by some terminals to reduce truck queuing at the terminal is to provide live views of their gates via webcams. An assumption made by the terminals in this method is that truck dispatchers and drivers will make rational decisions regarding their departure times such that there will be less fluctuations in truck arrivals at the terminal based on the live information. However, it is clear that if dispatchers send trucks to the terminal whenever the truck queues are short and not send trucks when the truck queues are long, it could lead to a perpetual whip lash effect. This study explores the predictive strategies that need to be made by the various dispatchers to achieve the desired effects (i.e. steady arrival of trucks and hence less queuing at the seaport terminal gates). This problem is studied with the use of an agent-based simulation model and the solution to the well known El Farol Bar problem. Results

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demonstrate that truck depots can manage (without any collaboration with one another) to minimize congestion at seaport terminal gates by using the provided real-time gate congestion information and some simple logics for estimating the expected truck wait time.

3.1 INTRODUCTION

Port drayage is defined as a truck pickup from or delivery to a seaport, with the trip origin and destination in the same urban area is a critical, yet comparatively understudied link in the intermodal supply chain (Harrison et al., 2007). Despite the relatively short distance of the truck movement compared to the rail or barge haul, drayage accounts for a large percentage, between 25% and 40%, of origin to destination expenses (Macharis and Bontekoning, 2004). High drayage costs seriously affect the profitability of an intermodal service which in turn could impede the advance of intermodal freight transportation. Hence, it is important to improve drayage operations to keep costs low. Another important reason to improve drayage operations is to reduce its emissions impact on the surrounding communities due to engine idling and the stop-and-go lugging. Reducing the idling time of drayage trucks is equivalent to reducing local and regional particulate matter (PM 2.5), nitrogen oxides, and greenhouse gas emissions. Because drayage trucks operate primarily in urban environments, a reduction of these harmful pollutants has a proportionally greater benefit.

One of the bottlenecks often incurred in port drayage operations is the pickup and delivery of containers from and to the marine terminal. During peak times at busy terminals, drayage trucks spend a significant time in the queues at the entry gate, container yard, and exit gate. The root cause of the excessive delays for

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drayage trucks is simply a function of supply (terminal resources) and demand (number of trucks). Given that resources (e.g. gates, clerks, yard cranes) at a terminal change very little on any given day, excessively long turn time for trucks is often the result of fluctuating truck arrivals. That is, because trucks come to the terminal at their earliest convenience without any prior announcement of their arrivals to the terminal operator, there are times during the day where the number of waiting trucks (demand) greatly exceeds the terminal's resources (supply). When demand greatly exceeds supply, truckers are forced to wait for their turn, resulting in engine idling and stop-and-go lugging. It should be noted that the truck arrivals are driven by shipper demands and ship schedules. Thus, there is a rational explanation for the observed peaking of truck traffic at the terminals.

One solution to the fluctuating truck arrivals is to employ an appointment system whereby the terminal operator designates available time windows for containers and subsequently truckers choose one of the available time windows. With an appointment system, the terminal operator could effectively control the truck arrival rates to keep its resources operating at the maximum level while at the same time ensuring timely service to the trucks. Recognizing the potential of this system, legislation in California suggested terminals to adopt the appointment system, among other methods, in an effort to reduce the number of trucks idling (California Assembly Bill 2650); the stated goal of this regulation was to reduce emissions. A subsequent bill (AB 1971) was passed in the summer of 2004 to include truck queuing. Hence, terminals in Los Angeles, Long Beach, and Oakland are subject to a $250 fine for each truck idling or queuing for more than 30 minutes while waiting to enter the terminal gate. Appointment systems are also employed by terminals outside of California (e.g. Port of Vancouver) and are under consideration at other US terminals.

In theory, the appointment system should improve the terminal's productivity

and reduce trucks' turn time. However, in practice, because of the lack of specific guidelines for implementing the appointment systems and that each U.S. terminal is left to manage their own system, the lack of structures in the appointment system has led to little time savings for truckers as reported in the work of Giuliano and O'Brien (2007). A similar conclusion was reached in a recently completed federal study which stated that "appointment systems are in an early stage of development, with no uniformity between terminals or ports and many implementation issues to be resolved" (Tioga Group et al., 2011). This problem of inefficiencies due to poor scheduling produce congestion, port staff overloads, unmet trucker needs, and general frustration. Given the present situation of high fuel costs and rising trucker discontent with port congestion, terminal operators seek to utilize as many low-cost solutions as possible. One such low-cost solution is to provide a live view of the gate condition via a webcam that can be accessible via the Internet. Implicitly, the terminal operators are assuming that dispatchers and truckers will utilize the provided information to their advantage; that is, not come during the peak periods. Hence, it is assumed that the truck arrival rates will have less variance and thereby reduces truck queuing at the terminal gates. To our knowledge, no research has been conducted to analyze the potential benefits or adverse effects of providing real-time gate congestion information. Through the use of agent-based simulation, this study seeks to examine ways which the dispatchers and truckers could take advantage of the provided real-time information such that their collective truck queuing time is minimal.

3.2 Background and Problem Description

This study models an actual real-world situation where truck dispatchers manage a set of trucks that need to go to the marine container terminal to either pickup an import container or deliver an export container. The dispatchers will periodically

Figure 3.1   Real-time view of gate condition via terminal webcam.

monitor the gate congestion condition and depending on the congestion level at the gate will send or withhold a truck at the depot. For example, if the dispatchers see that the terminal is busy, as shown in Figure 3.1, he/she may elect to have the truck make another move elsewhere instead of sending the truck to the terminal where it will likely have to wait for an extended period of time before receiving service. There are two important factors that affect the dispatcher's decision making. The first is the method which he/she uses to predict the expected waiting time for the truck when it gets to the terminal, and the second is the tolerance level that determines whether or not to send the truck.

The decision making process by the truck dispatchers is similar to that of individuals in the El Farol Problem. A brief summary of the El Farol Bar Problem and its solution are presented here. For additional details, readers are referred to the seminal work of Arthur (1994).

Suppose we have N people decide independently each week whether to go to a bar that offers entertainment on a certain night. Given that space is limited, so the

evening would only be enjoyable if the bar is not too crowded, say 60 people or fewer. There is no way to tell the numbers coming in advance; therefore, a person or agent goes to the bar if he expects fewer than 60 to show up or stays home if he expects more than 60 to go. Choices are unaffected by previous visits. There is no collusion or prior communication among the agents, and the only information available is the numbers who attended in past weeks.

Assume agents can individually form several predictors in the form of functions that map the past d weeks' attendance figures into next week's. Suppose recent attendance to the bar is:

...44, 78, 56, 15, 23, 67, 84, 34, 45, 76, 40, 56, 22, 35.

Possible predictors are: the same as last week's (35), a mirror image around 50 of last week's (65), or an average of the last four weeks (49).

The person decides to go or stay according to the currently most accurate predictor in his set. Once decisions are made, he learns the new attendance figure and updates the accuracies of his monitored predictors. In this bar problem, the set of predictors currently most credible and acted upon by the agents determines the attendance. But the attendance history affects the agents' set of predictors.

Similar to how Arthur modeled individuals in the El Farol bar problem as agents, in this study each truck dispatcher is modeled as an agent who has access to the real-time gate congestion information. At each time step, the dispatcher would predict the expected wait time, $E(W)$, using his/her set of predictors. If $E(W)$ is greater than the predefined wait time threshold, L, then the dispatcher would withhold the truck from departing for the terminal. If $E(W)$ is less than the threshold L, then the dispatcher agent would send the truck to the terminal. It should be noted that the decision making process of a truck dispatcher is much more complicated than that of individuals in the bar problem. The key differences are summarized in the following paragraph, and Section 3.4 discusses how we

extended Arthur's work to the gate congestion problem.

The terminal gate congestion problem addressed in this study seeks to understand the effects the predictive strategies, tolerance level, and operational related parameters have on the truck waiting time. Our goal is to design a decision making framework for the truck dispatchers that would produce steady demand at the marine terminal gate and also minimize waiting time for all trucks. It should be noted that the problem addressed in this study is more complex than the original El Farol Bar Problem. First, the total demand (number of people intending to go to the bar) does not vary with time, whereas the truck demands vary throughout the day. Second, the bar attendance event occurs at one specific time. In contrast, truck dispatching a continuous process that occurs throughout the operational hours of the terminal. Third, depots are not homogenous in that they are located at different distances to/from the terminal; depots that are closer to the terminal require less travel time to the terminal and hence are in a better position to take advantage of the provided real-time information because their expected wait time, $E(W)$ will be closer to the actual wait time. Fourth, drayage operations involve travel time and service time; these parameters are not applicable in the bar problem. Given that service time is stochastic, the predictive strategy of estimating truck wait time based on information is more difficult. In summary, terminal gate congestion problem addressed in this study is more complex in nature than the original El Farol Bar problem and thus finding the near-optimal solution is more challenging.

3.3   PRIOR RESEARCH

There is a vast amount of literature in the area of marine container terminal modeling. With rapid growth of containerization, container terminal operations are becoming more and more important and an increasingly rapid number of publications on container terminals have appeared in the literature. However, there

is limited work that deals specifically with strategies for managing marine terminal gate congestion. These works are addressed from either the drayage operator's or terminal operator's perspective. From the terminal operator's perspective, managing gate congestion can be accomplished via the use of a truck appointment system where truckers select from a given list of available time windows to arrive to pickup or deliver their containers. The terminal operators can better manage their workloads by controlling and limiting the available time windows. Work in this area include a study by Huynh and Walton (2008) who determined the maximum number of trucks a terminal operator could allow into its terminal based on available resources and investigated the effect of limiting the truck arrivals on the terminal's throughput and resource utilization. In a related study, Huynh (2009) explored rules for scheduling trucks to minimize total delays to trucks. Guan and Liu (2009) utilized a multi-server queuing model to analyze marine terminal gate congestion and quantified truck waiting cost. In the same study, they proposed an optimization model to balance the gate operating cost and truckers' cost due to excessive waiting time.

Unlike terminal operators who dictate how a terminal is run, the drayage operators are users who must follow the policies set by the terminal operators. Given their constraints, the drayage operators' primary aim is to avoid idling time at the terminals. They can accomplish this by scheduling their fleet to meet the appointment windows or avoid congestion periods. Work in this area include a study by Namboothiri and Erera (2008) who examined how a port's appointment-based access control system affects the management of a fleet of trucks providing container pickup and delivery service to a port. Similarly, Ioannou et al. (2005) investigated methodologies for the generation of optimum or near optimum time windows for cargo delivery/pickup at marine container terminals taking into account the objectives and constraints of the terminal operator and freight carriers.

Multi-Agent Systems (MAS) has become an important field within artificial intelligence research, and it has been successfully applied to applications such as control processes, mobile robots, air traffic management, and intelligent information retrieval. Far fewer applications are found in the areas of freight and intermodal transportation, in particular, seaport container terminals. To our knowledge, no study has examined the marine gate congestion problem from the MAS perspective.

3.4 METHODOLOGY

This section provides details regarding our formulation and implementation.

Formulation

A formal description of the problem is given here. There is a set of depots N and each depot $n \in N$ has a set of trucks T to send to the port in the planning period; the availability of containers (ready time for pick up of a container) associated with trucks follow a Poisson distribution with a mean of θ. All trucks are sent to a port P and $D(n, P)$ is the distance between the port P and the depot n. All depots are assumed to have the same fixed tolerance L which is the maximum wait time depots are willing to have their trucks $t \in T$ wait at the terminal gate. Also, depots are assumed to be able to estimate queuing time based on the number of trucks waiting at the gate; in the near future, it is conceivable that terminal operators will be able to provide queuing time information along with the live view, obtained either through GPS equipment on trucks or video image processing techniques). Trucks are withheld from departure for the terminal until a later time (when expected wait time is less or equal to tolerance i.e. $E(W) \leq L$). The intended pick up time of a container at the port by a truck is pickup-time(t). A boolean decision function SEND?(n, t) returns a value of 1 if depot n decides to

dispatch truck t to the port or 0 if it decides to withhold the truck. Once truck t is dispatched, it undergoes three different processes before it enters the terminal. The first process is making the trip to the port which takes time $T(t, P)$. Once a truck arrives in the vicinity of the gates, it picks a lane to enter. Here, we assume that truckers will select the lane with the shortest physical queue length (least number of trucks waiting in a lane). The second process is waiting in the queue. The actual queuing time of truck t is denoted as $Q(t)$. $Q(t)$ begins the instant when a truck joins the back of a queue and ends when the immediate preceding truck finishes its transaction. If no queue is present, $Q(t) = 0$. The third process is receiving service such as documentation processing at the gate. The service time of truck t is denoted as $S(t)$ which follows the Exponential distribution with mean r. A truck's wait time, $W(t)$, is $(Q(t) + S(t))$.

The dispatchers at depots make the SEND?(n, t) decision such that its truck can avoid excessive waiting at the terminal gate. The depot agents seek to accomplish this objective without any communication or collusion with other agents. In other words, the function SEND?(n, t) is internal to depot agents and its value is not disclosed to other agents when the decision is made. As previously defined, for all agents excessive wait time occurs when $E(W) > L$. The study period is discretized into uniform time intervals of length I. Let K be the number of trucks that finished their transactions at the gate during interval x. We defined the average truck wait time, $\overline{W}_x$ during the xth interval as follows.

$$\overline{W}_x = \frac{\sum_{k=1}^{K} W(k)}{K} \tag{3.1}$$

All depots are assumed to have access to historical truck waiting time at terminal gate for last m time intervals (i.e. agents' *memory* are limited to last m intervals). Starting with the xth time interval, the following history is available globally for all depot agents.

$$History_x = \{\overline{W}_{x-m}, ..., \overline{W}_{x-2}, \overline{W}_{x-1}\} \qquad (3.2)$$

However, it is possible that no trucks finished its transaction during interval x. In this scenario, we use a real-time estimate of truck wait time using a snapshot of the current demand at the gate. For instance, if at the beginning of xth time interval $\overline{W}_{x-1}$ is not available, then we compute $\overline{W}_{x-1}$ as follows.

$$\widehat{W}_{x-1} = (N_q + 1) \times r \qquad (3.3)$$

where N_q is the number of trucks in the shortest queue at the current time. Using the historical truck waiting time, at some x^{th} interval, the agents would estimate the time its truck has to wait at gate if it is dispatched at the onset of xth interval, $E(W)$. Note that the agents do not know the true $\overline{W}_x$ until $(x+1)^{th}$ interval. Depot agents carry out this prediction with the aid of internal models called *predictors*. Predictors are simple rules or logic (inductive reasoning) that can provide an estimate of $E(W)$ based on past trends or independently of past history. We use a large set of global predictor space, $S = [s^1, s^2, s^3, ..., s^z]$, which contains z predictors in total. Each depot agent $n \in N$ chooses randomly a fixed number of predictors, say k, from S and keeps a list of these predictors in my-predictors-list(n). However, as time progresses, agents learn how well each of his predictors is performing and will subsequently rank its predictors. The ranking information is recorded in a list named my-predictors-scores(n). This list maps score for each predictor into my-predictors-list(n). Also, all depot agents keep another list named my-predictors-estimates(n) that records estimates of $\overline{W}_x$ using each predictor in my-predictors-list(n). Note that the length of all three lists for each agent will be equal to k.

At the beginning of the xth interval, each depot agent applies the best performing predictor from my-predictors-list(n) to predict $\overline{W}_x$. This is referred as the

active predictor and is denoted as $s^{active-predictor}(n)$. The predicted value of $\overline{W}_x$ using $s^{active-predictor}(n)$ is denoted as $E(W)$. In deciding whether to send the truck at the xth interval, the depot agent applies the following logic.

1   **if** $E(W) \le L$

2   **then** SEND?$(n, t) = 1$

3   **else** SEND?$(n, t) = 0$

The global set of predictor models, S, employed in our work closely follows the set of strategies used by Garofalo (2006). A brief description of these strategies is given below:

- TitForTat: This family of strategies predicts next interval's attendance by using the same value as u weeks ago, with u from 1 to m.

- Mirror: This is a family of strategies using a mirror image around 50% of $2L$, with 1 to m intervals ago.

- Fixed: The Fixed strategy always chooses the same wait time estimate (10%, 20%, 30% ... or 200% of L).

- Trend: A u (1 to m) dated 2 intervals trend applied to the last interval.

- OppositeTrend: A u (1 to m) dated 2 intervals opposite trend applied to the last interval.

- Trend2: A u (1 to m) dated 2 intervals (3 interval spaced) trend applied to the last interval.

- MovingAverage: A u (1 to m) 5 intervals moving average.

- OppositeMovingAverage: A u ($1 to m$) opposite 5 intervals moving average.

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- Trend3: A u (1 to m) dated 2 intervals relative trend applied to the last interval.

- OppositeTrend3: A u (1 to m) dated 2 intervals relative trend applied to the last interval.

To update the performance (score) of the predictors in my-predictors-scores(n) which is subsequently used to determine $s^{active-predictor}(n)$, the three methods that are discussed in the literature are: absolute precision, relative precision, and original precision (Garofalo, 2006). In this study, we adopted the *original precision* approach. This approach was applied by Zambrano (2004), and according to him the evaluation function is the same as that was used in Arthur's seminal work. The original precision score updating method has the following form.

$$U_x(x^j(n)) = \alpha * U_{x-1}(s^j(n)) + (1-\alpha)|w_x^n(s^j(n)) - w_x| \qquad (3.4)$$

where $U_x(x^j(n))$ is the score of predictor j at x^{th} interval owned by agent n. $w_x^n(s^j(n))$ is the truck wait time estimation by predictor j at x^{th} interval by agent n. w_x is the actual wait time at x^{th} interval. α is a number strictly between zero and one. A low α gives more importance to recent performance while a high α gives more importance to past performance.

Implementation in Netlogo

The aforementioned methodologies were implemented in Netlogo, a multi-agent simulation framework (Wilensky, 1999). Netlogo facilitates experimentation and evaluation of the proposed paradigm. It provides many useful primitives (i.e. procedural commands) that are particularly suitable for this implementation. In our framework, depots and trucks are modeled as stationary and mobile agents, respectively. Figure 3.2 shows a screenshot of our model and graphical user
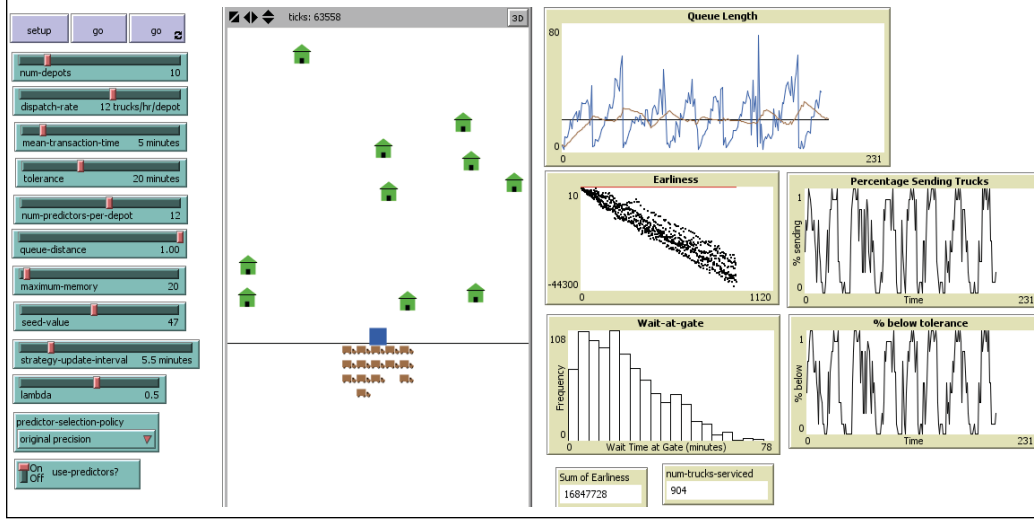
Figure 3.2   A screenshot of the Netlogo model evaluating terminal gate congestion.

setup()

1   create depot agents N and waiting lanes at terminal gate
2   set up a global predictor space S with $z = 200$
3   create and initialize $History_x$ of length m with random values
4   **for** each $n \in N$
5   **do** create trucks $t \in T$ for a 12 hour period with mean Poisson dispatch rate θ
6   create my-predictors-list(n) by randomly choosing k predictors from S
7   create and initialize my-predictors-scores(n) with zero score
8   create and initialize my-predictors-estimates(n) with random values

Figure 3.3   Setting up the simulation.

interface (GUI). As shown, the model provides several sliders for ease of changing the parameters on the fly. The parameters that could be changed directly on the GUI include the number of depots, truck dispatch rate, mean transaction time, tolerance, number of predictors per depot, maximum memory, interval length, α, etc. We developed a discrete event simulation where every tick (time-step) corresponds to one second of real-world time. The implementation has a one-time basic setup and a loop that is called at every tick. A pseudo code of the program is provided in Figures 3.3 and 3.4.

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loop()

  1 **while** there are truck to service by any depots in N
  2   **do** $tick \leftarrow tick + 1$
  3   **if** at beginning of xth interval
  4   **then** update $History_x$ with W_{x-1} and set length($History_x$) = m
  5   **for** each $n \in N$
  6   **do** update my-predictors-estimates(n)
  7   select $s^{active-predictor}(n)$
  8   determine E(W)
  9   **if** $E(W) \leq L$ and current time $\geq$ pickup-time(t) - $T(t, P)$ - $E(W)$
10   **then** SEND(n, t) = 1
11   **else** SEND(n, t) = 0
12   update my-predictors-scores(n)
13   update plots

14   **for** each $t \in T$
15   **do if** not at port
16   **then** move to port
17   **if** at port but not at head of queue
18   **then** move forward in queue
19   **if** at head of queue
20   **then** receive service with Exponential transaction time r
21   update plots

Figure 3.4   Main loop of the simulation.

3.5 Experimental Design

Experiments were performed using test problems with different combinations of mean transaction time (r), interval length (I) and tolerance (L). The test problems generates randomly chosen locations for depots and a container terminal at a seaport with five truck lanes at the gate. Once a truck is dispatched from the depot, the time required to travel to the port is deterministic and equals to the distance DISTANCE(n, P) divided by the truck's speed. When the truck arrives at the terminal gate, it picks a lane that has the least number of trucks waiting. The test parameters that were used for experiments are shown in Table 3.1. Some of these

Table 3.1   Values of parameters used in experiments.

Parameter	Value	Unit
Number of Depots	10	Nos
Dispatch rate (θ)	12	trucks/depot/hr
Mean transaction time (r)	3, 4, 5, 6, 7 and 8	minutes
Tolerance (L)	15, 20, 25 and 30	minutes
Total Number of predictors (z)	200	Nos
Number of predictors per depot (k)	12	Nos/depot
Update interval (I)	5,10 and 15	minutes
Maximum memory (m)	20	intervals
Predictor scoring policy	Original precision	n/a
α	0.5	n/a

parameters were kept constant and some were varied over realistic ranges to study how they influence the waiting time of trucks. Thirty replications are run for each combination of mean transaction time, interval length, and tolerance level. The performance measures recorded were (1) mean and (2) maximum waiting time of trucks during the study period, (3) Completion time (i.e. the time required to serve the demand of all depots (1440 trucks on average) during the study period. For comparative purposes, we also performed a base case run where depot agents do not utilize the provided real-time gate congestion information to dispatch trucks. That is, depot agents simply dispatch a truck when it is scheduled to go to the terminal without any regard for the current congestion level at the gate.

3.6   RESULTS

This section provides a summary and review of the results obtained from the described experimental plan. The overall results that show the effects of mean transaction time (r), interval length (I), and tolerance (L) on the truck wait time are summarized in Tables 3.2-3.6. In addition to providing the mean wait time, the maximum wait time of a truck and the completion *time* required to serve all the trucks T are presented. Note that the completion *time* is the time at which the last

Table 3.2 Mean wait, maximum wait and completion *time* for tolerance, $L = 10$ minutes.

r (min)	$I = 5$ minutes			$I = 10$ minutes			$I = 15$ minutes		
	mean (min)	max (min)	time (hrs)	mean (min)	max (min)	time (hrs)	mean (min)	max (mins)	time (hrs)
3	7.4	37.9	19.0	4.7	28.2	27.5	4.4	28.4	41.0
4	10.0	51.6	25.8	6.8	42.6	33.2	6.0	38.4	44.7
5	12.8	67.3	32.0	8.3	50.1	42.0	7.4	48.1	53.5
6	15.6	82.5	37.8	10.1	63.3	49.9	8.7	58.2	65.0
7	18.3	94.6	43.8	11.7	75.6	57.1	10.0	68.8	75.2
8	20.6	106.3	49.3	13.6	83.2	65.4	11.2	80.2	83.9

truck finished its transaction; it should be noted that unit of completion *time* is in hours whereas the mean and maximum wait times are minutes. These results are averaged over 30 simulation runs for five different tolerance levels (10, 15, 20, 25, and 30 minutes). At each tolerance level, three different interval lengths (5, 10, and 15 minutes) and six different mean transaction times (3, 4, ..., 8 minutes) are provided. The results from these tables indicate that as the mean service time r increases, the truck wait time increases, which is expected. Similarly, as the tolerance level increases, the truck wait time also increases. Again, this is also expected because dispatchers/truckers are willing to go to the seaport terminal even when they expect congestion. The interval length I can be interpreted as the frequency which the dispatchers check the terminal webcam and then make their SEND?(n, t) decisions. As shown in the results, the higher the frequency (i.e. smaller 'I' value), the higher the truck wait time. However, because the dispatchers effectively spread out the workload throughout the day the completion *time* increases as I increases.

Table 3.7 provides results for the case when L=15, but instead of making decisions at the beginning at each interval I, decisions by depots are made randomly over interval I. In comparison with the results in Table 3.3, it can be seen that asynchronous decision making provides an improvement over synchronous de-

Table 3.3 Mean wait, maximum wait and completion *time* for tolerance, $L = 15$ minutes.

r (min)	$I = 5$ minutes			$I = 10$ minutes			$I = 15$ minutes		
	mean (min)	max (min)	time (hrs)	mean (min)	max (min)	time (hrs)	mean (min)	max (mins)	time (hrs)
3	10.0	44.2	17.3	4.8	29.5	26.8	4.4	27.7	40.1
4	13.7	60.1	24.0	7.8	44.0	28.2	6.2	37.8	40.7
5	17.3	77.4	29.8	10.4	57.5	34.7	8.3	49.7	43.2
6	20.9	96.1	35.1	12.8	73.0	42.4	10.2	61.5	49.6
7	24.3	110.9	40.6	14.6	83.2	49.1	11.8	73.4	58.6
8	27.2	122.8	46.0	17.0	94.1	55.4	13.5	81.2	66.6

Table 3.4 Mean wait, maximum wait and completion *time* for tolerance, $L = 20$ minutes.

r (min)	$I = 5$ minutes			$I = 10$ minutes			$I = 15$ minutes		
	mean (min)	max (min)	time (hrs)	mean (min)	max (min)	time (hrs)	mean (min)	max (mins)	time (hrs)
3	13.0	50.2	17.1	4.8	30.2	26.8	4.4	28.5	40.1
4	17.4	68.9	23.3	8.1	45.0	27.0	6.3	40.6	40.2
5	22.1	89.9	29.1	12.1	58.6	31.4	8.6	50.9	40.8
6	26.7	110.1	34.3	15.1	75.1	38.7	11.2	62.1	43.8
7	30.2	128.6	39.4	17.9	95.5	45.2	13.6	77.6	50.9
8	33.7	143.9	44.1	20.4	100.5	51.7	15.6	92.2	58.4

Table 3.5 Mean wait, maximum wait and completion *time* for tolerance, $L = 25$ minutes.

r (min)	$I = 5$ minutes			$I = 10$ minutes			$I = 15$ minutes		
	mean (min)	max (min)	time (hrs)	mean (min)	max (min)	time (hrs)	mean (min)	max (mins)	time (hrs)
3	15.8	57.4	16.2	4.8	29.8	26.7	4.4	27.3	40.0
4	21.0	78.2	22.7	8.4	44.8	26.8	6.3	40.4	40.0
5	26.6	104.0	28.6	13.6	68.6	29.2	8.6	53.0	40.2
6	31.7	126.2	33.5	17.7	84.5	36.1	12.0	66.2	41.5
7	36.8	143.4	38.6	20.5	95.9	42.4	15.0	82.1	45.9
8	40.8	165.9	43.3	24.0	111.3	49.3	17.8	95.4	53.3

Table 3.6   Mean wait, maximum wait and completion *time* for tolerance, $L = 30$ minutes.

r (min)	$I = 5$ minutes			$I = 10$ minutes			$I = 15$ minutes		
	mean (min)	max (min)	time (hrs)	mean (min)	max (min)	time (hrs)	mean (min)	max (mins)	time (hrs)
3	18.6	62.2	16.1	4.8	30.4	26.7	4.4	29.7	40.0
4	24.8	89.5	22.6	8.2	45.3	26.8	6.2	38.8	40.1
5	31.0	112.1	28.2	15.6	69.6	28.3	8.7	54.7	40.2
6	37.7	136.6	33.4	20.4	88.9	34.9	12.3	64.0	40.7
7	42.8	157.6	38.2	24.1	110.1	41.9	16.5	84.3	43.7
8	47.2	176.7	43.0	27.5	121.4	47.9	19.7	99.1	49.8

Table 3.7   Mean wait, maximum wait and completion *time* for tolerance, $L = 15$ minutes (Asynchronous Case).

r (min)	$I = 5$ minutes			$I = 10$ minutes			$I = 15$ minutes		
	mean (min)	max (min)	time (hrs)	mean (min)	max (min)	time (hrs)	mean (min)	max (mins)	time (hrs)
3	8.1	37.1	16.0	3.2	24.9	26.6	3.0	24.8	39.9
4	11.2	50.1	20.9	4.8	37.8	27.7	4.1	33.1	40.9
5	13.4	63.1	25.9	7.5	47.1	31.2	5.4	40.6	42.1
6	15.5	75.0	30.6	9.7	64.4	36.6	7.1	47.9	44.9
7	17.8	87.8	34.8	11.6	73.5	41.0	8.7	59.1	49.8
8	18.1	93.8	41.4	12.7	77.1	48.6	10.0	66.4	58.1

cision making which is more like to be the case in practice. That is, although the terminal operator may update the queuing information every 5 minutes, not all truck dispatchers will make their dispatch decisions immediately after that information is available. It's more likely that such decisions occur randomly over some interval; in this study, we assume that interval is I.

Figure 3.5, Figure 3.6, and Figure 3.7 show how the mean wait time, maximum wait time and completion *time* vary over different tolerance levels, respectively. In all three plots the results are shown for a mean transaction time of 5 minutes and interval lengths of 5, 10 and 15 minutes. For all three update intervals, the general trend is that the mean and maximum wait time increases with higher tolerance
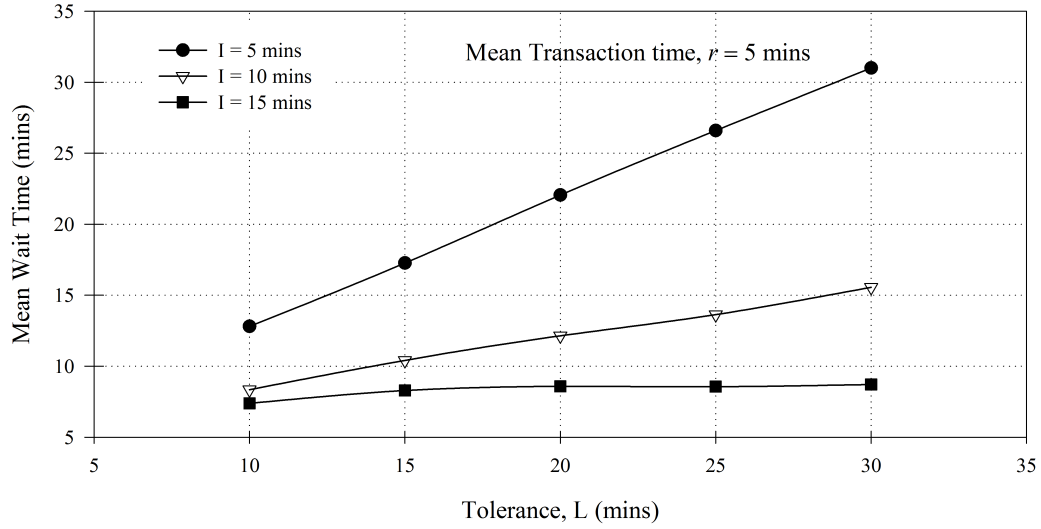
Figure 3.5   Impact of tolerance on mean wait time of trucks.

levels, *L*(as shown in Figures 3.5 and 3.6). However, the rate of increase is higher when *I* is lower. When *I* = 5 minutes, as the tolerance level increases the truck wait time increases linearly. However, when *I* = 15 minutes, as the tolerance level increases, there is very little change in truck wait time. It is interesting to note that *I* nullifies the effect of *L*.

As explained, the total completion time follows a contrasting pattern. That is, it decreases as the tolerance level increases. Note that when *I* = 5 minutes, the completion *time* is always lower than when *I* =10 and 15 minutes, which means that all trucks got served in a short amount of total time. What the completion *time* results suggest is that when truck dispatchers monitor the webcam more frequently and consequently send trucks to the seaport terminal if the gate is not congested, there is more opportunities for that dispatchers to send trucks; hence, shorter completion *time*.

Figures 3.8 and 3.9 show the mean wait time history for the study period for two particular runs from the experiments. Figure 3.8 shows the results for a mean transaction time *r* of 8 minutes and *I* and *L* of 15 minutes. In Figure 3.9, *r* is 6 minutes, and *I* = *L* = 10 minutes. These plots also include a base line identifying
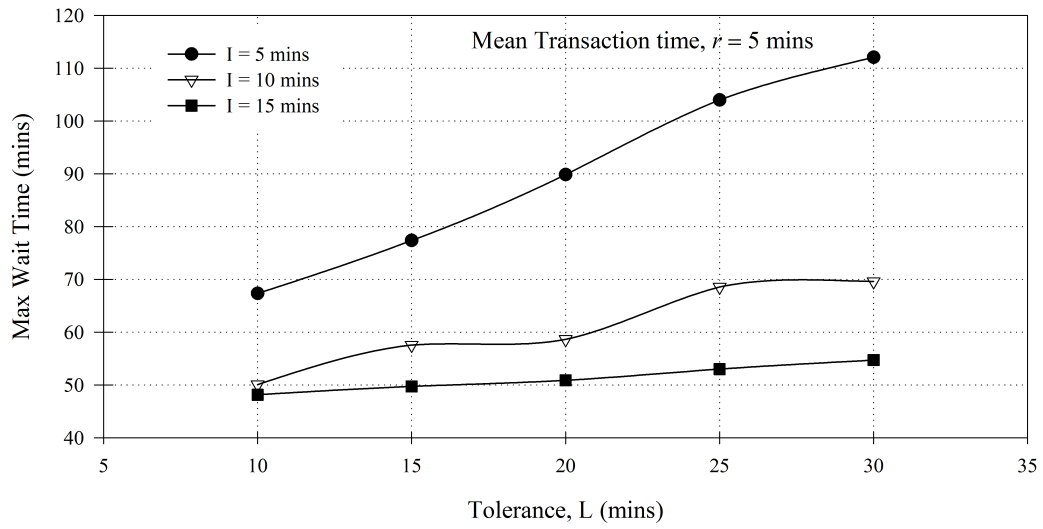
49

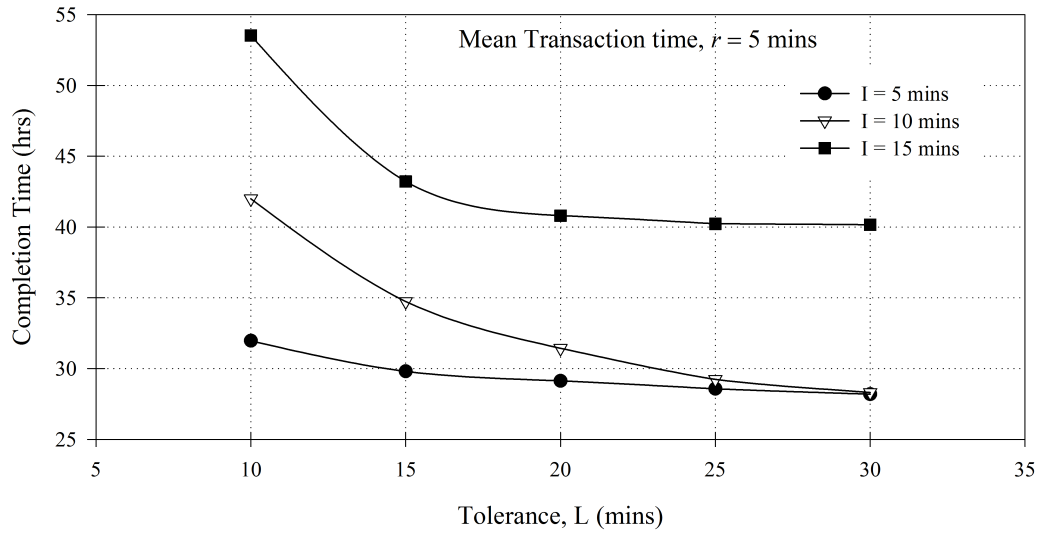Figure 3.6　Impact of tolerance on maximum wait time of trucks.

Figure 3.7　Impact of tolerance on total completion time.

tolerance level to demonstrate the convergence characteristics of the truck wait times. Our results show that the convergence does not occur for some scenarios. For instance, if the selected combination of parameters from Table 3.1 impose low demand on the gate (e.g. $I = 15$ minutes, $r = 3$ minutes, and $L = 15$ minutes), all depot agents will use the predictor that predicts a wait time lower than tolerance. Thus, every depot agent ends up sending trucks, but the demand they create at the gate does not exceed the gate capacity; hence, the truck wait time $\overline{W}_x$ at different intervals x will never exceed the tolerance level L. Another interesting finding that was observed in our analysis is that when convergence does occur, the mean wait time constantly fluctuates about the tolerance level. This is in contrast to original El Farol Bar problem where the mean attendance converges to the tolerance level (60) after some time. We believe this difference stems from the fact that the gate congestion problem is far more complex than the original problem (see end of section 3.2). Nevertheless, in using nearly the same set of predictive strategies, we were able to show that depot agents could potentially make independent decisions such that they all benefit in the end by having lower total truck wait time. Perhaps, with some modifications of the existing predictors or design some new predictors one could achieve the same convergence characteristic as the original bar problem.

Table 3.6 provides results for the scenario where no predictors are used in dispatch decisions by the depot agents. This represents a base case for comparison to assess the benefit of using the proposed paradigm to manage gate conges- tion. Note that we have reduced the dispatch rate from 12 trucks/hr/depot to 6 trucks/hr/depot for these runs because the former value induces very high demand of trucks at the gate and the benefits of our proposed approach might be over-emphasized. For a more fair comparison, another set of experiments was conducted where agents employ the same predictors, but for a reduced dispatch rate of 6 trucks/hr/depot. The mean transaction time is 5 minutes in both cases.
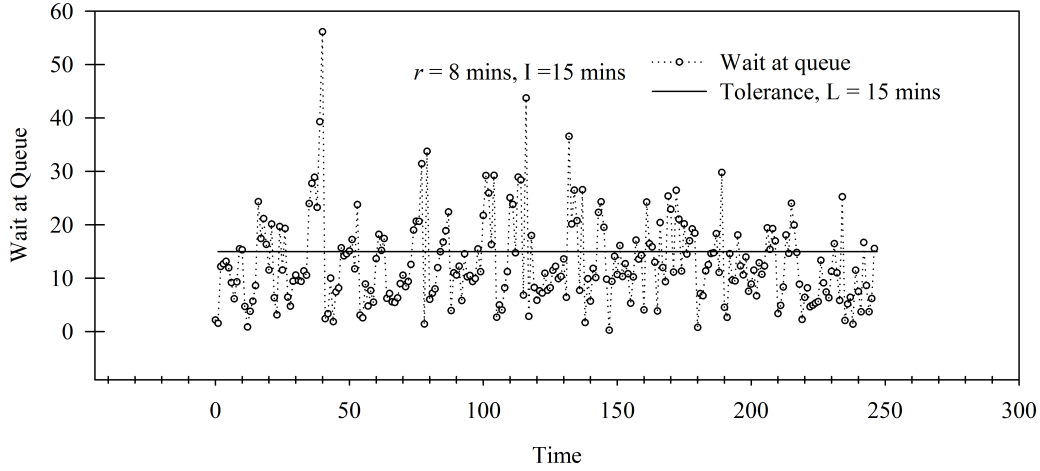
Figure 3.8   Mean wait time of trucks plotted every 15 minutes interval with 15 minutes tolerance.
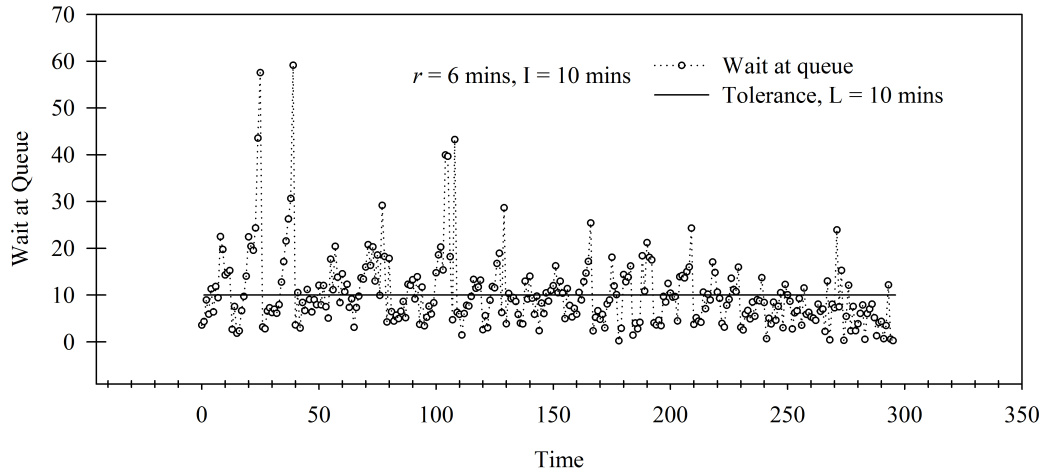
Figure 3.9   Mean wait time of trucks plotted every 10 minutes interval with 10 minutes tolerance.

A tolerance level of 15 minutes and an interval length of 5 and 10 minutes were selected. The comparison results are shown in Figure 3.10. These results show that our model yields 43% and 63% lower mean wait time for an interval of 5 and 10 minutes, respectively. Similarly, the reduction in maximum wait time is 22% and 40%, respectively. However, the total completion time is higher, by about 18% and 40% for the two intervals, respectively.

Figure 3.11 plots a typical histogram found for any combination of r, I, and L.

r (mins)	Mean (mins)	Max (mins)	Completion time (hrs)
5	26.6	86.4	12.8

Figure 3.10   Results showing wait time and completion time with and without using predictive strategies.

Figure 3.11   Histogram of waiting time of truck for r = 5 minutes, I = 5 minutes, and L = 10 minutes.

Table 3.8   Percentage decrease in emission.

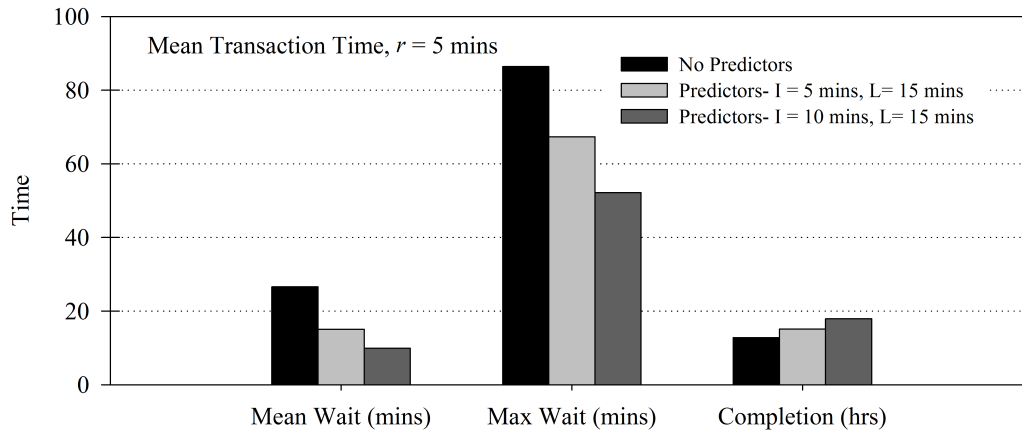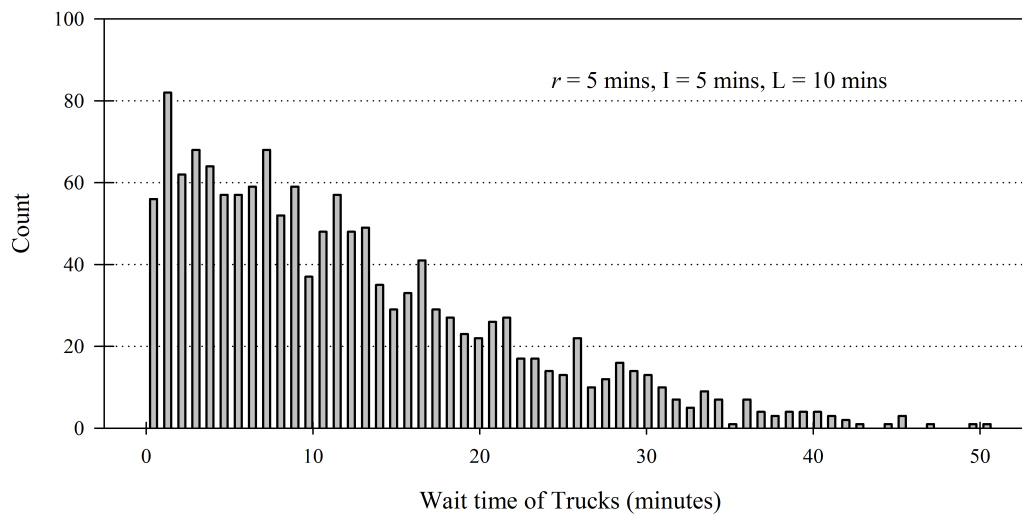| Pollutant	$I = 5, L = 15$	$I = 10, L = 15$
HC	2.30%	3.40%
CO	2.40%	3.50%
NO_x	1.70%	2.40%
PM_{10}	1.50%	2.20%
PM_{25}	1.50%	2.20%
CO_2	1.60%	2.30%

The shown distribution of truck wait times from our simulation model matches that of empirical data collected from actual terminals. The results from Figure 3.11 highlight the extent of the marine terminal gate congestion problem. As shown, a good portion of the trucks spend more than 10 minutes queuing (i.e. idling and stop-and-go lugging) at the gate. This represents a serious environmental issue. Emissions from diesel engines of drayage trucks can cause a critical share of local and regional particulate matter (PM 2.5), nitrogen oxides (NOx) and greenhouse gas (GHG) emissions. Also, according to the EPA, PM 2.5 emissions from diesel engines are a serious health concern. Thus, reducing the average inbound gate queueing time will likely lead to a reduction in emissions as well as fuel and cost savings for trucks. To quantify the benefit in terms of emissions reduction using our proposed paradigm to manage gate congestion, a simple emissions analysis was performed. Table 3.8 summarizes the comparative results found using the SmartWay DrayFLEET model, developed by EPA in collaboration with the Federal Highway Administration. The results in Table 3.8 correspond to a dispatch rate of 6 trucks/depot/hr and mean transaction time of 5 minutes.

3.7   Conclusions and Future Work

Truck queuing during peak periods at marine terminal gates has long been identified as a critical emission sources due to extensive idling of diesel engine trucks.

Though some remedial measures are employed, their benefits are still largely unknown and published research is very limited. To this end, this paper presents an agent-based approach where depots can manage (without any collaboration with one another) to minimize congestion at seaport terminal gates by using the provided real-time gate congestion information and some simple logic for estimating the expected truck wait time.

Our work is inspired by the well known El Farol Bar problem, but we have modified the methodology and implementation to account for the additional complexity and dynamics involved with truck dispatch and queuing at terminal gates. Our simulation model implementation contains a handful of parameters that attempts to capture all the variables that are relevant to the gate congestion problem. Extensive experiments were conducted by using practical ranges of the parameters. The results demonstrate that the depots can effectively and successfully minimize truck wait time at the terminal gate by adopting our proposed framework by distributing the demand more uniformly over the operational hours (i.e. adopt a higher I). Our findings also reveal how the selection of different parameters in our model will impact the average and maximum wait time of trucks, as well as how depots can benefit from extended operational hours. Results from our simple emissions analysis show that a good amount of emissions reduction can be gained over the base case (do nothing) scenario.

We have comprehensively evaluated all the parameters and their values relevant to the gate congestion problem. However, given that this is the first study of its kind, which addressed a complex real-world problem, additional studies are needed to fully understand the problem. From the experiments we performed in this study, it appears that a pool of 200 predictive strategies with each depot agent employing 12 predictors is sufficient. Our experience shows that the higher these two numbers the better. However, we have yet to explore whether it is practical for

a dispatcher to have 12 or more predictive strategies. Another interesting line of research would be to incorporate more sophisticated learning models to determine if they would improve the overall system performance.

What we have found from this study is that the different depot agents will have to use different strategies. If they all use the same strategy then either they all will end up sending their trucks to the port or all will withhold the trucks, resulting in a continuous fluctuation in truck arrivals at the port. To apply this approach in practice, it must be ensured that (1) each depot uses a set of predictors that are capable of forecasting a decent range both above and below the tolerance level, and (2) the depots must not share identical set of predictors (i.e. there must be adequately different type of predictors from depot to depot).

AN AGENT-BASED SOLUTION FRAMEWORK FOR

INTER-BLOCK YARD CRANE SCHEDULING PROBLEMS[1]

ABSTRACT

The efficiency of yard operations is critical to the overall productivity of a container terminal because the yard serves as the interface between the landside and waterside operations. Most container terminals use yard cranes to transfer containers between the yard and trucks (both external and internal). To facilitate vessel operations, an efficient work schedule for the yard cranes is necessary given varying work volumes among yard blocks with different planning periods. This paper investigated an agent-based approach to assign and relocate yard cranes among yard blocks based on the forecasted work volumes. The goal of our study is to reduce the work volume that remains incomplete at the end of a planning period. We offered several preference functions for yard cranes and blocks which are modeled as agents. These preference functions are designed to find effective schedules for yard cranes. In addition, we examined various rules for the initial assignment of yard cranes to blocks. Our analysis demonstrated that our model can effectively and efficiently reduce the percentage of incomplete work volume for any real-world sized problem.

Keywords: Yard crane scheduling, container terminals, multi-agent systems, deferred acceptance algorithm.

4.1 Introduction

The importance of marine container terminals in international trade has been well documented (Vis and de Koster, 2003; Steenken et al., 2004; Stahlbock and VoB, 2008). Previous studies have also reported planning and operational challenges that port authorities and terminal operators have to contend with at marine container terminals (Murty et al., 2005; Rashidi and Tsang, 2006; Henesey, 2006). Capacity constraints, lack of adequate decision making tools, congestion, and environmental concerns are some of the issues facing terminals today. Various operations research techniques, automated equipment, and information technology have been applied in an effort to improve the efficiency of various terminal operations with limited resources and high workloads. An important problem that has been studied extensively is how to expedite vessel operations (Steenken et al., 2004). To this end, researchers have investigated the quay crane scheduling problem, transporter scheduling problem, and yard crane scheduling problem (Rashidi and Tsang, 2006). This study focuses on the yard crane scheduling problem. It deals with the planning problem of appropriate locations for yard cranes and where to move them during vessel operations to facilitate the unloading of import containers and loading of export containers.

The container yard at a marine terminal serves as a buffer for import containers before they are picked up by a drayage truck and for export containers before they are loaded onto a vessel. Figure 4.1 depicts a simplified layout of a marine container terminal- the land side gates for external truck operations, the yard for container storage and the quay side for vessel operations. The yard is typically made up of multiple yard zones and each zone with multiple yard blocks. A
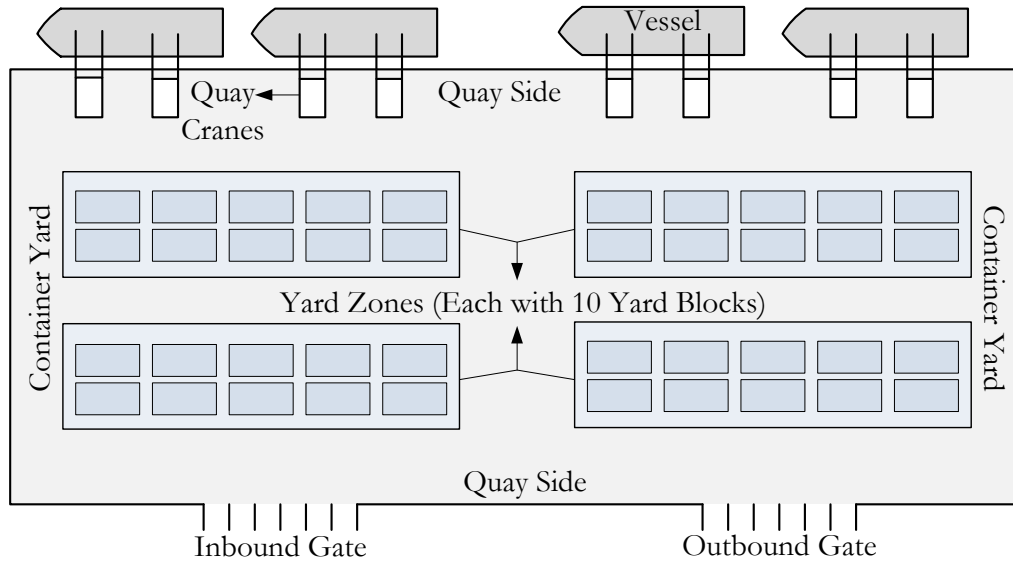
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Figure 4.1   Illustration of a container yard layout. (Not to scale)

typical block at a U.S. terminal is forty 40-foot bays long, 6 rows wide and 4 containers high Huynh and Vidal (2012). There are two types of yard cranes, rubber tired and rail mounted. Rail-mounted yard cranes move on rails and they can only travel in one direction (along the length of block). Rubber tired yard cranes are more flexible in that they can move in both directions. They are the more popular choice among U.S. terminals. The yard crane scheduling problem addressed in this study assumes the use of rubber-tired yard cranes. A rubber tired yard crane is shown in Figure 4.2.

During vessel operations, the yard cranes need to be able to keep up with the quay cranes as they load and unload containers from the vessel. The amount of work in each block depends on whether the vessel is being unloaded or loaded. During the unloading operation, import containers are unloaded from the vessel and stored in designated import yard blocks, and during the loading operation, export containers are retrieved from specific export yard blocks and loaded onto the vessel. Typically, a number of unloading and loading operations will take place during vessel operations that will require the yard cranes to be in various

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Figure 4.2   A rubber-tired yard crane on work.

yard blocks. Thus, an efficient yard crane deployment plan is necessary to address variable work volume and is imperative in lowering the vessel turn time. Vessel turn time refers to the time a vessel spent at a terminal while awaiting the unloading and loadings of containers. The vessel turn time is one of the chief indicators of a terminal's productivity and competitiveness. The inter-block yard crane deployment problem is as follows: given the forecasted work volume of each block in each period of a day, assign the yard cranes among blocks dynamically so that the total incomplete work volume in the yard is minimized. This scheduling problem historically has been addressed by mathematical optimization programs (A review is available in Section 4.2). In contrast, this study utilizes an agent-based approach. Agent-based modeling is a decentralized and a relatively new research field within the realm of artificial intelligence. Researchers and practitioners in many disciplines, from biology to economics, have developed agent-based models, and the number of applications continues to rise (Bernhardt, 2007). While

agent-based modeling and Multi-Agent Systems (MAS) have been applied in many different disciplines, they are relatively unexplored in the area of port operations.

There has been no study using a decentralized approach to solve the inter-block crane deployment problem. The typical advantages of adopting an agent-based approach over classical optimization include the capability of solving problems of large sizes through discretization, producing a time efficient solution, obtaining a solution adaptive to changes in a dynamic system, and obtaining a robust system with better computational stability (Davidsson et al., 2003). Additionally, in recent years integrative modeling for container terminals are being emphasized which is based upon the fact that various processes in a terminal are interconnected and improved terminal performance cannot necessarily be achieved by treating the processes separately (Stahlbock and VoB, 2008). Therefore, there is a need to integrate models of various terminal processes with one another. Only a few studies have attempted such an integrated approach. However, the scope of these studies is limited in that only a few selected operations are considered together, and the focus is primarily on the quayside processes. More decision tools need to be developed and integrated. Multiagent systems approach has been proposed as a tool in integrated decisions frameworks in works by Thurston and Hu (2002); Henesey (2006); Franz et al. (2007). Our model may serve as a component tool in an integrated multi-agent model. In past work, we have developed agent-based models related to gate operations and real-time yard crane scheduling (Sharif et al., 2011; Huynh and Vidal, 2010). The model described in this study can be combined with these previously developed models to develop an integrated model. Such an integrated model is not viable using traditional optimization techniques due to computational complexity. Also, our agent-based approach to the yard crane deployment model is easier to understand because it uses simple intuitive preference functions for agents. These preference functions are designed to quickly

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find effective schedule for cranes. In addition, we examined various rules for the initial assignment of cranes to blocks. Furthermore, in this study, we assessed some simple strategies for an initial assignment of cranes to yard blocks to provide guidance for the terminal operator or stevedore.

4.2 RELATED STUDIES

There is a vast amount of literature in the area of marine container terminal modeling. With container terminal operations becoming more and more important, an increasing number of publications on container terminals have appeared in the literature. A survey of container terminals related research can be found in several sources: Vis and de Koster (2003); Steenken et al. (2004); Stahlbock and VoB (2008); Crainic and Kim (2007); Murty et al. (2005); Rashidi and Tsang (2006); Vacca et al. (2007); Henesey (2006). A comprehensive review is beyond the scope of this paper.

Yard operations, in general, involves two classes of decision problems, namely, 1) storage space assignment problem - the objective is to determine an optimum space allocation such that handling and re-handling of containers is kept at a minimum and traveling time of vehicles is minimized. Types of operations such as 'wheeled' and 'stacking' operations, land utilization, and efficient accessibility of containers are some factors generally taken into account (Vis and de Koster, 2003); and 2) scheduling problem of yard equipment such as yard cranes used for container storage, retrieval and reshuffling operations - the objective is to maximize utilization of cranes and minimize unfinished work volume, completion time of tasks and waiting time of transport vehicles in a planning period. The review in this section is primarily focused on literature addressing the latter problem i.e. yard crane scheduling at marine container terminals. Existing studies involving scheduling of yard cranes can further be divided into two subgroups, as they consider decision making at two different levels: 1) assigning yard cranes to

blocks (crane-to-block) and 2) assigning yard cranes to trucks (crane-to-truck). The 'crane-to-block', also frequently called 'inter-block yard crane deployment problem', involves the dynamic allocation of yard cranes to various storage blocks. This subgroup aims at optimizing the movement of yard cranes among blocks. In contrast, the 'crane-to-truck' involves determining the optimal sequence of handling of individual containers i.e. serve individual trucks, which deals with the real-time bay to bay movement of cranes. Although both 'crane-to-block' and 'crane-to-truck' are decision problems considered at the operational level (i.e. short-term planning), the former usually needs to be solved at longer periodic intervals (typically every several hours), while the latter typically needs to be solved at shorter periodic intervals (typically several times within an hour) or in real-time.

One of the earliest studies on inter-block yard crane deployment is by Zhang et al. (2002). The focus of the study was to, given the forecasted work volume of yard blocks in each period of a day, find the times and routes of crane movements among yard blocks so that the total delayed work volume in the yard is minimized." They formulated a Mixed Integer Program (MIP) for dynamic deployment of yard cranes and solved the program using Lagrangean relaxation. In another study by Cheung et al. (2002), they addressed the deployment problem with the same objective. The formulation was also an MIP which was shown to be NP-hard and a new solution approach called 'successive piecewise-linear approximation method' was developed, which is more effective and efficient than the Lagrangean decomposition. Linn et al. (2003) presented an algorithm and a mathematical model for the optimal yard crane deployment. The effectiveness of the model was tested against a set of actual operation data collected from a major container terminal in Hong Kong. Linn and Zhang (2003) developed a least cost heuristic algorithm to find a near optimal solution of practical size crane deployment

problems. Yan et al. (2008) presented two heuristic algorithms, the hill-climbing algorithm and the best-first-search algorithm, to overcome the NP-hardness of the deployment problem. He et al. (2010) employed a hybrid algorithm, which combines heuristic rules and parallel genetic algorithm. A simulation model was also developed to evaluate their approach.

Kim et al. (2003) used simulation to study various truck serving rules for yard cranes to minimize truck delay. The sequencing rules comprise dynamic programming, first-come-first- served, unidirectional travel, nearest-truck-first-served, shortest-processing time rule, and a rule set from reinforcement learning. Ng and Mak (2005) studied the problem of scheduling a yard crane to handle a given set of jobs with different ready times. They proposed a branch and bound algorithm to solve an MIP that finds an optimal schedule that minimizes the sum of truck waiting times. In a follow-up study by Ng (2005), the author extended his previous work to deal with multiple yard cranes instead of a single yard crane. His model accounted for interference among cranes which may occur when they are sharing a single bi-directional traveling lane. An integer program was proposed and a heuristic was developed to solve the model. Lee et al. (2007) studied the scheduling of a two yard crane system which serves the loading operations of one quay crane at two different container blocks, so as to minimize the total loading time at stack area. A simulated annealing algorithm was developed to solve the proposed mathematical model. Li et al. (2009) developed a crane scheduling model where operational constraints such as fixed yard crane separation distances and simultaneous container storage/retrievals are considered. The model was solved using heuristics and a rolling-horizon algorithm. Huynh and Vidal (2010) introduced an agent-based approach to schedule yard cranes with a specific focus on assessing the impact of different crane service strategies on drayage operations. In their work, they modeled the cranes as utility maximizing agents and developed

a set of utility functions to determine the order in which individual containers are handled.

In this paper we address the crane-to-block level of decision making which is known as the 'inter-block crane deployment problem'. The contributions of this study to the literature are: 1) provides an agent based framework for solving the inter-block crane deployment problem, 2) provides an approach that effectively minimizes the percentage of incomplete work volume, 3) provides a scalable and time efficient approach, and 4) provides various strategies of initial assignment of yard cranes.

4.3 Methodology

This section provides details regarding our assumptions and inter-block crane deployment model.

Assumptions

The assumptions are as follows-

- The total operational hours of a container terminal is divided into several shifts or planning periods. The planning periods can be of equal or different time lengths.

- A forecast of the work volumes in the yard blocks are known at the beginning of the planning period.

- For the safety of crane operations, at any time at most two cranes can work in the same block.

- An idling yard crane at some block can be relocated to assist another block, but such transfer is only allowed once per planning period. This assumption is to avoid traffic congestion in the yard area.

- For each block the *initial work volume* at the beginning of a planning period is the work volume forecast for that period plus incomplete work volume from the previous period.

- The transport vehicles (Internal Trucks or Automated Guided Vehicles) moving between storage yard and quay cranes does not introduce delay in yard cranes' operation.

- The capacity of RTGCs are identical and equal to length of planning period (measured in time units).

- When the number of container moves in a yard block is known, Equation 4.1 is used to obtain work volume in time units for that block. The parameter 'Average time units required per move' required in Equation 4.1 can be estimated by a container terminal (i.e. 'total time required by yard cranes to handle a number of containers' divided by 'total number of containers handled' gives how much time on average is required per move).

Work volume = Average timeunits required per move × Number of container moves

$$(4.1)$$

The transfer time of a yard crane between two blocks are calculated in the following manner. If a yard crane is relocated to a block for which it needs to travel in a longitudinal direction with respect to its current location, the transfer time is 10 minutes for each block traversed. For example, in Figure 4.3, if a yard crane is relocated from block $B2$ to $B8$, it takes (3×10) or 30 minutes to complete the transfer. If a yard crane is relocated to a block for which it also needs to travel
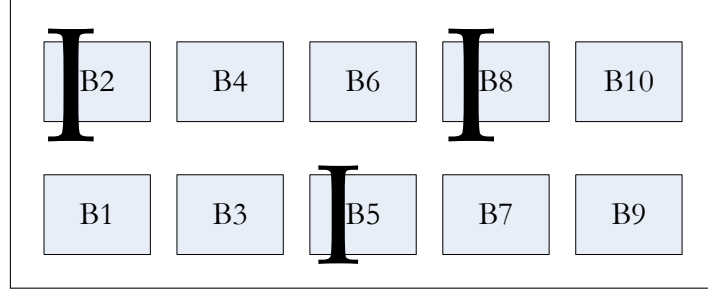
Figure 4.3   Illustrating the transfer time of cranes.

in a transverse direction with respect to its current location, the transfer time is 10 minutes for each block traversed plus 5 minutes for an additional two 90 degree turns of the crane wheels. If a yard crane is relocated from block $B2$ to $B5$, it takes $(5 + 2 \times 10)$ or 25 minutes to complete the transfer.

Initial Assignment of yard cranes

At the beginning of a planning period, the container yard manager must decide on the initial distribution of yard cranes among the yard blocks. The initial assignment of yard cranes can be simply random or uniformly distributed among the blocks. However, a more reasonable assignment will be that based on work volume forecasts in the blocks at the beginning of a planning period. The studies in literature dealing with the inter-block deployment problem assumes that an initial assignment of the cranes are given or known (which, in reality, is usually based on the judgement of the yard manager). However, in our study we have investigated some intuitive strategies that can be employed for the initial assignment. These strategies are presented in this section. Note that a good strategy shall be tailored to achieve objectives such as: 1) assign cranes to blocks where they are most needed i.e. based on work volume and 2) reduce the number of future inter-block crane transfers during operation to prevent loss of time and crane productivity. We address these goals in three approaches namely 'high to low work volume',

'crane at each block', and 'reduce transfers'.

For illustration we use the following variable definitions-

$T_c \equiv$ Capacity of a crane c in time units (length of planning period)

$IW_b \equiv$ Initial work volume of a block b at the beginning of a planning period

$NC_b^{initial} \equiv$ Number of cranes initially assigned to a block b at the beginning of a planning period

$NC_b^{current} \equiv$ Number of cranes currently assigned to a block b i.e. its value may change over operational hours

$NC_b^{max} \equiv$ Maximum number of cranes that can work in a block b simultaneously (The value of NC_b^{max} is set to 2 in our model)

High to low work volume In this strategy, a list of blocks is generated by sorting the blocks in the order of decreasing IW_b. Thus, the topmost item of the list has the maximum work volume and the bottommost item has the minimum work volume. Then, cranes are assigned to blocks according to their order in the list starting with the topmost item. Once a block is assigned NC_b^{max} cranes, the next block in the list is considered for assignment, and the process is continued until all available cranes are assigned. Note that this simple strategy does not directly take into account the actual value of work volumes but only their relative order in the list.

Crane at each block In this strategy three possible scenarios are considered. Let total number of cranes be n_c and total number of blocks be n_b.

- If $n_c = n_b$, assign a single crane at each block.

- If $n_c < n_b$, generate a list of blocks sorted in order of decreasing IW_b. Then assign a single crane to each of the top n_c blocks from that list.

- If $n_c > n_b$, first assign a single crane in each block. Then calculate the

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incomplete work volume for all blocks using Equation 4.2.

$$\text{Incomplete work volume of block } b = IW_b - T_c \qquad (4.2)$$

Now, create a list of blocks sorted in decreasing order of *incomplete work volume* as found from Equation 4.2. Next assign a single crane to each of top $n_c - n_b$ blocks from that list.

Reduce transfers This strategy assign cranes to blocks in following steps-

- Find the blocks that satisfy Equation 4.3. For these blocks, assign NC_b^{max} cranes in each block.

$$IW_b \geq NC_b^{max} \times T_c \qquad (4.3)$$

- Next, find the blocks that satisfy Equation 4.4. For these blocks, assign a single crane in each block.

$$IW_b < NC_b^{max} \times T_c \text{ and } IW_b \geq T_c \qquad (4.4)$$

- Calculate the incomplete work volume for the blocks using the following Equation 4.5.

$$\text{Incomplete work volume of block } b = IW_b - T_c \times NC_b^{current} \qquad (4.5)$$

Then, find the blocks that satisfy the following condition in Equation 4.6.

$$NC_b^{current} < NC_b^{max} \text{ and Incomplete work volume of block } b \geq 0.7 \times T_c$$
$$(4.6)$$

Next, create a list of these blocks sorted in order of decreasing work volume as found in Equation 4.5. Assign a single crane to each block from top of that list and continue until there are cranes available. Note that the factor '0.7' in Equation 4.6 is a measure of how much need there

is for a block to have an additional crane. This factor should be between 0.66 to 1.0. For our study we used 0.7 which produces the best results in our model.

- If additional unassigned cranes are available, compute the revised incomplete work volume for blocks using Equation 4.5. Then create a list of these blocks sorted in order of decreasing work volume for which Equation 4.7 holds true.

$$\textit{Currently assigned number of cranes} < NC_b^{max} \qquad (4.7)$$

Next assign a single crane to each block starting from the top of that list and continue until there are cranes available. Repeat this step until all remaining cranes are assigned.

Pre-Analysis steps

Once a decision on the initial assignment is made, the cranes will be appointed to their designated blocks at the beginning of the planning period. The next step is to determine the inter-block crane transfers during operations of the planning period. However, before we move to that step of the analysis, we can exclude some blocks and cranes from that step. This simplification is a set of reasonable assumptions, inclusions and exclusion procedures that are also used in previous studies. These procedures effectively reduce the size of the crane deployment problem. The following paragraphs describe how the blocks and cranes are identified to be *excluded* from or *included* into further analysis.

- We *exclude* a block if it has the maximum number of cranes initially assigned to it and its work volume equals or exceeds the capacity of those initially assigned cranes. Clearly the block cannot accommodate any additional cranes and its currently assigned cranes need to stay at that block till the

end of the planning period. Thus, we can also *exclude* the cranes initially appointed at the block from analysis for they will not be transferred to other blocks.

- We *exclude* a block if its work volume is equal to the capacity of the initially assigned crane or cranes since the block does not require any additional cranes. Also, we can *exclude* the cranes appointed to that block from analysis since the crane or cranes will not be transferred to other block.

- We *exclude* a block if its work volume is less than the capacity of its initially assigned crane or cranes, obviously the block does not require any additional cranes. However, the cranes have extra capacity left after finishing work in that block and can be transferred to help out in other blocks. Therefore we *include* these cranes in further analysis. The extra capacity of the cranes depends on how much work volume each crane shares in that block. If we limit the sharing to a minimum we can save time spent on transfers. The extra capacity of a crane c initially assigned at a block b can be computed using Equation 4.8.

$$E(c) = T_c \times NC_b^{initial} - IW_b \tag{4.8}$$

- We *include* a block if it has less than the maximum number of cranes that can be initially assigned to it and its work volume exceeds the capacity of initially assigned cranes. Under this situation the block needs help and can accommodate additional crane or cranes transferred to it from other blocks. However, the cranes that are already located in this block are needed for the entire period and thus we can *exclude* them from further analysis. The amount of help needed or the incomplete work volume of a block b can be computed using Equation 4.9.

$$H(b) = IW_b - T_c \times NC_b^{current} \tag{4.9}$$

After the above steps are carried out the deployment problem will consist of a set of blocks needing help that can accommodate additional cranes and set of cranes with extra capacity available for helping out other blocks.

Dynamic deployment of cranes

A formal description of the problem is given here. Let us consider that the deployment problem consists of a set of blocks B and a set of cranes C. Each block $b \in B$ has a strict preference ordering over the cranes in C and each crane $c \in C$ has a strict preference ordering over the blocks in B. The preference ordering of a block i is denoted as $\succ_b^i$ and $c^x \succ_b^i c^y$ means block i ranks crane x above crane y. Similarly, the preference ordering for crane j is $\succ_c^j$. We want a matching between agents in B and C, which means an assignment of cranes to blocks satisfying these constraints 1) each crane can be matched/assigned to at most one block, and 2) one block can be matched/assigned to one or more cranes but not exceeding NC_b^{max}.

Preference functions for agents

We present in this section some strategies to generate preference orderings for agents. Once the preferences are available they can be used in subsequent application of the algorithm. Note that, a good preference strategy encourages 'crane-block' matchings that will likely minimize the total incomplete work volume at the end of a planning period. We have investigated four different strategies, namely, 'Minimum transfer time', 'Positive difference', 'Absolute difference' and 'Absolute difference squared distance'.

Minimum transfer time In this strategy, the preference orderings for cranes and blocks are determined by transfer time required to relocate a crane c from its origin block o to destination block d which we denote as TT_c^{od}. This is

a greedy approach that only considers transfer time. In contrast to other strategies we investigated, it does not take into account the extra capacity of a crane or the amount of help needed by a block. A crane simply prefers to be transferred to a block that is closest to its current block and a block prefers to attract a crane that is currently located in a block closest to it. The preference for a crane c over a block b is computed as in Equation 4.10-

$$\succ_c = TT_c^{od} \tag{4.10}$$

The preference for a block b over a crane c is computed as in Equation 4.11-

$$\succ_b = TT_c^{od} \tag{4.11}$$

Using the above equations, the preference ordering for a crane or a block agent over agents in B or C respectively can be obtained by sorting agents yielding minimum to maximum value. Any tie is broken arbitrarily or randomly. If the extra capacity of a crane is less than or equal to the transfer time to a block then the transfer is invalid and both the crane and block pair will remove each other from preference ordering.

Positive difference In this strategy, the preference ordering for cranes and blocks is determined by (1) transfer time required to relocate a crane from its origin block to destination block, (2) extra capacity of a crane (3) the amount of help needed by a block. The preference for a crane c over a block b is computed using Equation 4.12.

$$\succ_c = E(c) - H(b) - TT_c^{od} \tag{4.12}$$

The preference for a block b over a crane c is computed using Equation 4.13.

$$\succ_b = E(c) - H(b) - TT_c^{od} \tag{4.13}$$

Using the above equations, the preference ordering for a crane or a block agent over agents in B or C respectively can be obtained by sorting agents yielding maximum to minimum value. Any tie is broken arbitrarily or randomly. A positive preference value implies that if the crane is relocated to a block, it will finish all the unfinished work there and will have some idle time. A negative preference value implies that if the crane is relocated to a block, it will only finish a portion of the unfinished work with no idle time. The idea underlying this preference function is to finish all work in a block, however a large positive value implies significant unused crane time. If the extra capacity of a crane is less than or equal to transfer time to a block then the transfer is invalid and both the crane and block pair will remove each other from the preference ordering.

Absolute difference In this strategy, similar to 'positive difference', the preference ordering for cranes and blocks is determined by (1) transfer time required to relocate a crane from its origin block to destination block, (2) extra capacity of a crane (3) the amount of help needed by a block. However, we take the absolute of preference values. The preference for a crane c over a block b is computed using Equation 4.14.

$$\succ_c = |\ E(c) - H(b) - TT_c^{od}\ | \tag{4.14}$$

The preference for a block b over a crane c is computed using Equation 4.15.

$$\succ_b = |\ E(c) - H(b) - TT_c^{od}\ | \tag{4.15}$$

Using the equations, the preference ordering for a crane or a block agent over agents in B or C respectively can be obtained by sorting agents yielding minimum to maximum value. Any tie is broken arbitrarily or randomly. A small preference value implies that after transfer time is deducted from the

extra capacity of a crane it closely matches to the help needed by a block. A large preference value implies a large difference, that is, if the crane is relocated to a block, it will either finish all incomplete work but at the cost of significant idling or can only finish a small portion of the incomplete work volume with no idling. The idea underlying this preference function is to encourage matching of a crane and a block pair for which extra capacity is close to incomplete work volume. If the extra capacity of a crane is less than or equal to transfer time to a block then the transfer is invalid and both the crane and block pair will remove each other from preference ordering.

Absolute difference squared distance In this strategy, similar to 'absolute difference', the preference ordering for cranes and blocks is determined by (1) transfer time required to relocate a crane from its origin block to destination block, (2) extra capacity of a crane (3) the amount of help needed by a block. However, we take the square of the transfer time to accentuate its effect on the preference values. The preference for a crane c over a block b is computed using Equation 4.16.

$$\succ_c = \mid E(c) - H(b) - (TT_c^{od})^2 \mid \tag{4.16}$$

The preference for a block b over a crane c is computed as follows-

$$\succ_b = \mid C(c) - H(b) - (TT_c^{od})^2 \mid \tag{4.17}$$

Using the above equations, the preference ordering for a crane or a block agent over agents in B or C respectively can be obtained by sorting agents yielding maximum to minimum value. Any tie is broken arbitrarily or randomly. The idea underlying this preference function is the same as 'absolute difference', that is, to encourage matching of a crane and a block pair for which extra capacity is close to the incomplete work volume. However,

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since long transfer time of a crane translates to a high loss in the crane's productivity, we aim to discourage moves involving long transfer times using a squared value. If the extra capacity of a crane is less than or equal to the transfer time to a block then the transfer is invalid and both the crane and block pair will remove each other from the preference ordering.

An algorithm to assign cranes to blocks

Since we are interested in assigning the cranes to blocks, we can view the problem as if we are 'matching' cranes with blocks (or vice versa). In other words, a crane matched to a block is essentially assigning the crane to block. The reason why we want to treat the task of assignment as a 'matching problem' is because then we can use an algorithm that is similar in construction as 'deferred acceptance algorithm' (DAA). The DAA is a matching model first introduced by (Gale and Shapley, 1962) in their famous paper "College admission and stability of marriage". Since the paper was published it has generated numerous follow up studies by researchers in Economics and Computer science. DAA has been applied to various real world matching problems such as assigning students to schools, people to jobs, nurses to residencies etc. DAA is able to find a match between two sets of agents in a two-sided market, where each set of agents have preferences over the other set of agents to which they wish to match. The basic idea of DAA is that the agents from one side of the market propose, in their order of preferences, to the agents on other side of market. Then the set of agents receiving the proposals review and reject (also in their order of preferences) and final acceptance is deferred until the last step of the DAA. For detailed information regarding the algorithm and various relevant theoretical results to date see Roth (2008). DAA have two versions depending on which side of the market are proposing. Another variation of the model is 'one-to-one' matching vs. 'many-to-one' matching. A marriage model

is an example of a one-to-one matching since each man is matched to at most one woman or vice versa, whereas a college admission model is a many-to-one matching problem since each student can be matched to at most one college but a college can be matched to more than just one student. An important note is that matching algorithms are generally studied in context of their 'stability' property, which is not in our interest. DAA does not provide any mechanism to generate preferences for agents, it is assumed that true preferences of agents are known. We assume that the preferences functions we offered for the cranes and blocks are their true preferences.

For the inter-block deployment problem we use an algorithm similar to many-to-one matching version of DAA because in a planning period a crane can be matched to only one block while a block can be matched to more than one crane. We present two versions of our algorithm here, namely (1) crane proposing version (2) block proposing version. For illustration of algorithm, we define 'quota' q_i for a block i as the maximum number of cranes a block can hold at some time minus the number of cranes currently located in the block i.e. $(NC_b^{max} - NC_b^{current})$. From the previous section we know that, each crane has strict preferences defined over the set of blocks, and each block has strict preferences defined over the set of cranes, and a matching is to be determined that will assign each crane j to no more than one block, and each block i to no more than q_i cranes.

Crane proposing version Consider the following steps:

1. Each crane j proposes to first block i from its preference list (if crane j's preference list is not empty).

2. Each block i receiving more than q_i proposals, 'holds' the most preferred q_i cranes and rejects all others.

n. Each crane j rejected at step $n - 1$ removes the block i rejecting the crane from its preference list. Then rejected crane j makes a new proposal to its

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next most preferred block i who hasn't yet rejected it. (if crane j's preference list is not empty). Go to step $n - 1$.

Stop: when no further proposals are made, that is, no cranes are rejected or the rejected cranes preference list is empty.

Finally, match the blocks to the cranes whose proposals they are holding. (if any)

Block proposing version Consider the following steps:

1. Each block i proposes to its most preferred q_i cranes from its preference list (if block i's preference list is not empty).

2. Each crane j who received at least one proposal, 'holds' the most preferred block and rejects all others.

n. Each block j who is rejected by one or more cranes at step $n - 1$ will remove those cranes from its preference list. Let, the number of rejections a block j has received is r_j. The rejected block j makes a new proposal to its next r_j preferred cranes to whom the block has not proposed already (if crane j's preference list is not empty). Go to step $n - 1$.

Stop: when no further proposals are made, that is, no blocks are rejected or the rejected blocks' preference lists are empty.

Finally, match the cranes to the blocks whose proposals they are holding. (if any)

A sample example

In this section we review how our model solves a sample crane deployment scenario. The scenario is illustrated in Figure 4.4 that considers a problem with 10 yard blocks (rectangles) and 15 yard cranes (I shaped footprints) and the layout is as shown. Block IDs are preceded with the letter 'B' and crane IDs are preceded with the letter 'C'. The work volume for a block at the beginning of a planning

period in minutes is shown within the parenthesis. The length of planning period is 4 hours or 240 minutes. The initial distribution of 15 yard cranes to 10 blocks is obtained using the 'reduce transfers' assignment strategy, which is the location of cranes at the beginning of the planning period as shown in Figure 4.4a. Then we run the pre-analysis steps to find out the blocks and cranes that will participate in further analysis. There are 5 cranes with available extra capacity and they are C11, C14, C16, C18 and C19 (shown in bold face). Also there are 5 blocks that needs help and they are B0, B2, B3, B5 and B7 (in bold face). Now we generate preference lists for these cranes and block agents using 'minimum transfer time' strategy. The lists are:

$\succ_{CRANE11}$: block 0 $\succ$ block 3 $\succ$ block 2 $\succ$ block 5 $\succ$ block 7

$\succ_{CRANE16}$: block 7 $\succ$ block 5 $\succ$ block 2 $\succ$ block 3 $\succ$ block 0

$\succ_{CRANE14}$: block 5 $\succ$ block 2 $\succ$ block 3 $\succ$ block 7 $\succ$ block 0

$\succ_{CRANE19}$: block 7 $\succ$ block 5 $\succ$ block 3 $\succ$ block 2 $\succ$ block 0

$\succ_{CRANE18}$: block 7 $\succ$ block 5 $\succ$ block 2 $\succ$ block 3 $\succ$ block 0

$\succ_{BLOCK3}$: crane 11 $\succ$ crane 14 $\succ$ crane 16 $\succ$ crane 19 $\succ$ crane 18

$\succ_{BLOCK0}$: crane 11 $\succ$ crane 14 $\succ$ crane 16 $\succ$ crane 18 $\succ$ crane 19

$\succ_{BLOCK2}$: crane 14 $\succ$ crane 11 $\succ$ crane 16 $\succ$ crane 18 $\succ$ crane 19

$\succ_{BLOCK5}$: crane 14 $\succ$ crane 16 $\succ$ crane 11 $\succ$ crane 19 $\succ$ crane 18

$\succ_{BLOCK7}$: crane 16 $\succ$ crane 19 $\succ$ crane 14 $\succ$ crane 18 $\succ$ crane 11

Next we apply the algorithm in Section 4.3 to solve for matching using the crane proposal version which yield the following matching- (block 0, crane 11); (block 3, crane 19); (block 2, crane 18); (block 7, crane 16); (block 5, crane 14). The final locations of the cranes after transfer to their matched blocks are shown in Figure 4.4b. For all blocks the work volume is zero at the end of the planning period. Thus percentage incomplete workload is also zero. If we used the mathematical
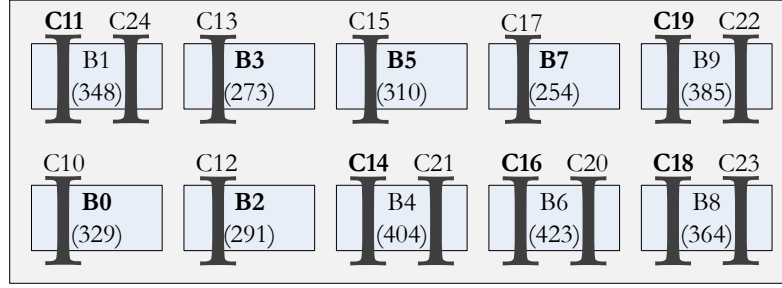
(a) Initial State of yard at the beginning of planning period
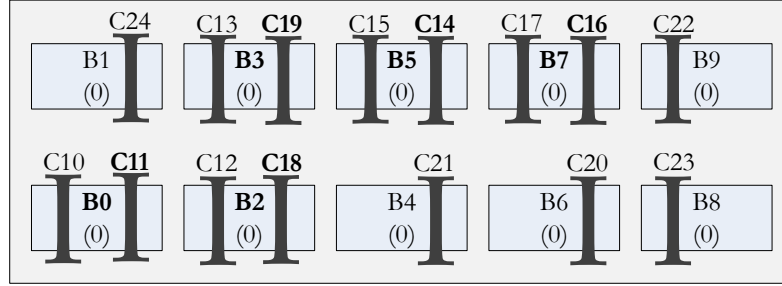
(b) Final State of yard at the end of planning period

Figure 4.4   A sample crane deployment scenario

program proposed by Linn et al. (2003) we would obtain the same results. For the majority of the cases our model is able to find optimal or near-optimal solutions. This is evident from Tables 4.2 and 4.3 where percentage incomplete work volume found by our model is close to mathematical program. Note that, some of the preferences in this example are symmetric, that is, the crane's first choice is a block whose first choice is the crane (e.g. Block 0 and Crane 11; Block 7 and Crane 16; Crane 14 and Block 5). It may appear that we do not need the algorithm to find the crane-block pairs, since we can just put the cranes in their preferred blocks. However this is not always the case. Notice that Block 3 and Block 0 both wants Crane 11; Block 0 gets it because it is the first item of Crane 11's list; Block 3 ends up getting 4th choice). This example uses the same preference strategies for block and crane agents. However, we can pick different preference strategies; for example, the cranes may use 'minimum transfer time', whereas the blocks may use 'absolute difference'.

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4.4 Implementation and Results from Experiments

The aforementioned methodologies were implemented in Netlogo, a multi-agent simulation framework (Wilensky, 1999). Netlogo facilitates experimentation and evaluation of the proposed paradigm. It provides many useful primitives (i.e. procedural commands) that are particularly suitable for this implementation. In our framework, blocks and cranes are modeled as stationary and mobile agents, respectively. Figure 4.5 shows a screenshot of our model and graphical user interface (GUI). As shown, the model provides several sliders for ease of changing various parameters. The parameters that could be changed directly on the GUI include the number of blocks, number of cranes, work volume level, selection of initial crane assignment strategy, and preference functions for agents. The implementation consists of the following steps in sequence:

1. Setup the layout of blocks

2. Choose a work volume level for the planning period

3. Generate work volume for each block

4. Create cranes

5. Choose initial crane assignment strategy

6. Assign the cranes to blocks

7. Compute inter-block travel time and the transfer time matrix

8. Run the pre-analysis steps to filter blocks and cranes that will participate in further analysis

9. Choose between block proposal and crane proposal version
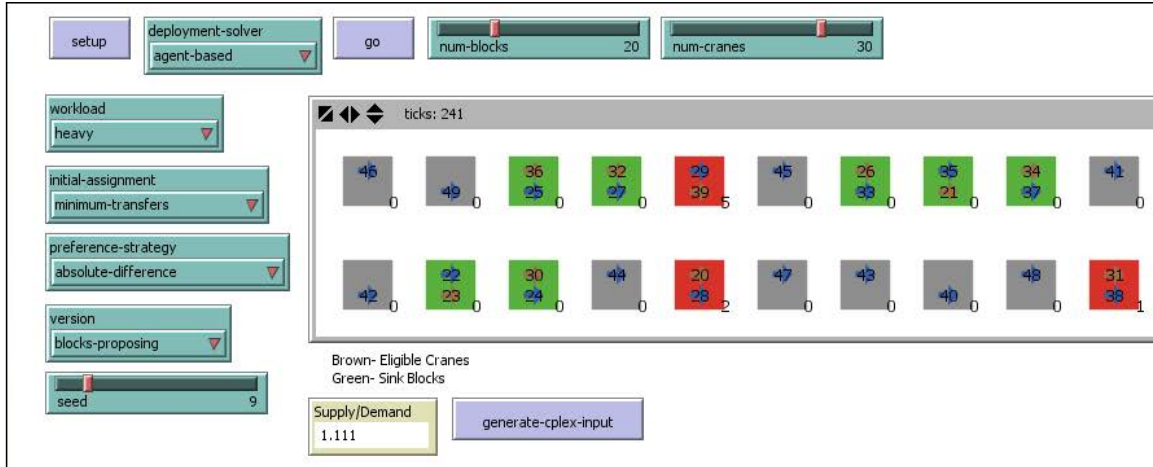
10. Run the chosen version and solve for matching

Figure 4.5   A screenshot of the agent-based model.

11. Reassign cranes according to the solution

12. Update graphics and record results

We tested our model against various real-world sized crane deployment problems. The test parameters that were used for experiments are shown in Table 4.1. Some of these parameters describing the size of the problem are varied over realistic ranges. Other parameters are various options to modify the steps of analysis. Fifty replications are run for combinations of the test parameters. The performance measures recorded were total incomplete work volume and total crane idling at the end of the planning period. For comparative purposes, we also performed a run where a centralized mathematical program developed by Linn et al. (2003) is used to solve the test problems. As shown in Table 4.1, the highest number of blocks in our experiment is 30, a case which is comparable to a fairly large real world problem. As the number of blocks becomes large in a container terminal, the yard area is partitioned into multiple yard zones, each yard zone consisting of a group of blocks. In practice the yard cranes are not moved from one zone to another zone in a planning period. The numbers of cranes were set to be equal to the number of blocks or 50% higher than the number of blocks. To assign the work

Table 4.1   Values of parameters used in experiments.

Parameter	Value	Unit
Number of blocks	10, 20, 30	Nos
Number of cranes	1 or 1.5 × Number of blocks	Nos
Length of planning period	240	Minutes
Work volume	(1) Moderate (2) Heavy (3) Above capacity	Minutes
Initial assignment	(1) Random (2) Crane at each block (3) High to low work volume (4) Reduce transfers	-
Preference strategy	(1) Minimum transfer time (2) Absolute difference (3) Positive difference (4) Absolute inverse squared distance	-
Version	(1) Blocks proposing (2) Cranes proposing	-

volume to blocks in a planning period, various assignment procedures or work volume severity (supply-demand ratio) is assumed. Work volume condition has two parts 1) total work volume of blocks compared to capacity of all cranes and 2) distribution of work volume among the blocks. Table 4.1 lists three different work volume conditions- moderate, heavy and above capacity. *Moderate* work volume condition implies that the total work volume is 60% of the total available crane capacity. Total available crane capacity is the number of cranes times the capacity of a single crane. The distributions of work volume among the blocks are such that work volume can be 40% higher or lower than the average work volume per block. Average work volume per block is the total work volume divided by the number of blocks. *Heavy* work volume conditions imply that the total work volume is 90% of the total available crane capacity. The distributions of work volume among the blocks are such that the work volume can be 20% higher or lower than the average work volume per block. *Above capacity* work volume condition implies that the total work volume is 110% of the available crane capacity. The distributions of work volume among the blocks are such that work volume can be 40% higher or lower than the average work volume per block. The rest of the parameters of Table 4.1 (i.e. initial assignment, preference strategy and version) and their values are as described in Section 4.3.

Table 4.2 Percentage incomplete work volumes: Case I- Average number of cranes per block = 1.0

Number of Blocks		10			20			30	
Number of Cranes		10			20			30	
Work Volume	M	H	AC	M	H	AC	M	H	AC
Minimum Transfer Time	0	0.13	11.34	0	0.10	11.14	0	0.12	11.28
Absolute difference	0	0.16	12.16	0	0.13	12.09	0	0.11	12.16
Positive difference	0	0	13.55	0	0.05	13.08	0	0.04	12.86
Absolute difference squared distance	0	0.13	11.80	0	0.08	11.69	0	0.10	11.81
Mathematical Program	0	0	10.57	0	0	10.57	0	0	10.60

Table 4.3 Percentage incomplete work volumes: Case II- Average number of cranes per block = 1.5

Number of Blocks		10			20			30	
Number of Cranes		15			30			45	
Work Volume	M	H	AC	M	H	AC	M	H	AC
Minimum Transfer Time	0	0.02	9.79	0	0.20	10.00	0	0.48	10.04
Absolute difference	0	0.07	10.19	0	0.18	10.45	0	0.43	10.48
Positive difference	0	0.14	10.40	0	0.53	10.73	0	1.00	10.71
Absolute difference squared distance	0	0.01	10.06	0	0	10.31	0	0.01	10.38
Mathematical Program	0	0	9.69	0	0	9.77	0	0	9.79

In Tables 4.2 and 4.3 the percentage incomplete work volumes are listed for various cases in the experiments. The column headings 'M', 'H' and 'AC' refer to 'medium', 'heavy' and 'above capacity' work volume conditions. The percentage of incomplete work volume at the end of a planning period can be computed as in Equation 4.18.

$$Percent\ incomplete\ work\ volume = \frac{Initial\ Work\ Volume - Finished\ Work\ Volume}{Initial\ Work\ Volume} \times 100\%$$

(4.18)

We show results for those combinations of parameters that provide the best performance from our model i.e. minimize the total incomplete work volume of blocks at the end of the planning period. The results in Table 4.2 and 4.3 are based on 'Reduce transfers' chosen as initial assignment since this strategy produces

the best results. Also, the results are not influenced by the 'version' of algorithm such as 'Cranes Proposing' or 'Block Proposing' because as long as we use the same preference strategy for block agents and crane agents, the results will be indifferent. For 'medium' condition the percentage incomplete work volume is always zero no matter what preference functions we use or the size of the problem. For 'heavy' conditions, the percentage incomplete work volume is also very low and always less than or equal to 1% remaining unfinished. For 'above capacity' conditions, the percentage of incomplete work volume is also very promising, within 3% of the optimal solution found by mathematical program. Note that in the above capacity condition demand exceeds supply, therefore it is not possible for the cranes to complete all work volumes. In fact, even if we disregard the time loss by transferring cranes among blocks, it can be easily shown that there will always remain at least 9.1% of the work volume incomplete. For this case the 'minimum transfer time' preference function appears to be consistently the best strategy.

Our model was created using Netlogo version 4.1.3 running on a personal computer with 2.57GHz Centrino dual-core CPU and 4 Gigabytes of RAM. The experiments were run using the 'BehaviorSpace', a tool integrated with NetLogo. The computation time to find a solution using our deployment algorithm is very short; a problem with 10 blocks can be solved in less than a second, and a problem with 30 blocks can solved in less than 3 seconds.

4.5 Conclusion and Future Work

This paper presented a study on the inter-block crane deployment problem in a marine container terminal. The deployment problem is an integral part of the daily decision making for terminal operators and stevedores. The goal of our study was to best utilize the capacity of cranes to minimize the work volume that remains

incomplete. We explored various strategies for how to assign the cranes among blocks at the beginning of a planning period based on the work volume forecast. Adopting an agent-based approach, we presented preference functions to generate preferences for crane and block agents. These preference functions are intuitive and constructed based on the parameters that influence the best utilization of cranes' capacities. We applied the deferred acceptance algorithm based on these preferences of agents to establish effective relocations of cranes during a planning period. The results showed that our model provides an excellent solution in short time for a range of work volume conditions with high variation. In 'medium' condition all work can be finished within planning period, in 'heavy' condition the percentage remaining incomplete is less than or equal to 1%, in 'above capacity' condition the percentage remaining incomplete is within 3% of the optimal. Our model is scalable to large sized problems; a test case with 30 blocks can be solved within 3 seconds.

There are a number of ways in which this work could be extended. In future work, we plan to consider relocating cranes multiple times within a planning period. In this study, we limited the relocation of yard cranes to once per crane per planning period. In addition, we plan to extend the model to include forecasts for multiple planning periods in making deployment decisions. Another direction this research could be taken is to solve the integrated problem involving the inter-block crane scheduling with quay crane scheduling and/or drayage truck scheduling.

STORAGE SPACE ALLOCATION AT MARINE

CONTAINER TERMINALS USING ANT-BASED CONTROL[1]

ABSTRACT

This paper presents a novel approach for allocating containers to storage blocks in a marine container terminal. We model the container terminal as a network of gates, yard blocks and berths on which export and import containers are considered as bi-directional traffic. For both export and import containers, the yard blocks are the intermediate storage points between gates (landside) and berths (waterside). Our model determines the route for each individual container (i.e. assign the container to a block to be stored) based on two competing objectives: 1) balance the workload among yard blocks, and 2) minimize the distance traveled by internal trucks between yard blocks and berths. The model utilizes an ant-based control method. It exploits the trail laying behavior of ant colonies where ants deposit pheromones as a function of traveled distance and congestion at the blocks. The route of a container (i.e. selection of a yard block) is based on the pheromone distribution on the network. The results from experiments show that the proposed approach is effective in balancing the workload among yard blocks and reducing the distance traveled by internal transport vehicles during vessel loading and

unloading operations.

5.1 INTRODUCTION

The importance of marine container terminals in international trade has been well documented (e.g. Vis and de Koster, 2003; Steenken et al., 2004; Stahlbock and VoB, 2008), and many studies have discussed the planning and operational challenges that port authorities and terminal operators have to contend with at container terminals (e.g. Murty et al., 2005; Rashidi and Tsang, 2006; Henesey, 2006). Capacity constraints, lack of adequate decision making tools, congestion, and environmental concerns are some of the major issues facing terminals today. This study aims to provide a decision making tool to aid port authorities and terminal operators in addressing the storage space allocation problem (SSAP).

A simplified layout of a marine container terminal is presented in Figure 5.1. The layout shows the waterside where vessel operations take place, the yard for container storage, and the landside where gate operations take place. The container yard serves as a temporary storage area for import and export containers. The storage of containers in the yard is unavoidable because of the time difference between the landside and waterside operations. Export containers from customers are brought to the terminal by external trucks (XTs) and are stored in the yard until they are loaded onto a vessel. On the other hand, import containers are unloaded from berthed vessels by quay cranes and are brought into the yard by internal trucks (ITs) where they are stored until they are picked up by an XT. The container yard is typically divided up into areas known as yard blocks. Each yard block holds a group of containers which are laid side by side on the ground and also stacked on top of one another (in stacked terminals). The equipment deployed at

the yard blocks to handle containers is known as yard cranes which carry out the storage, pickup and reshuffling operations. The time period a container is stored in the yard is known as storage period or dwell time.
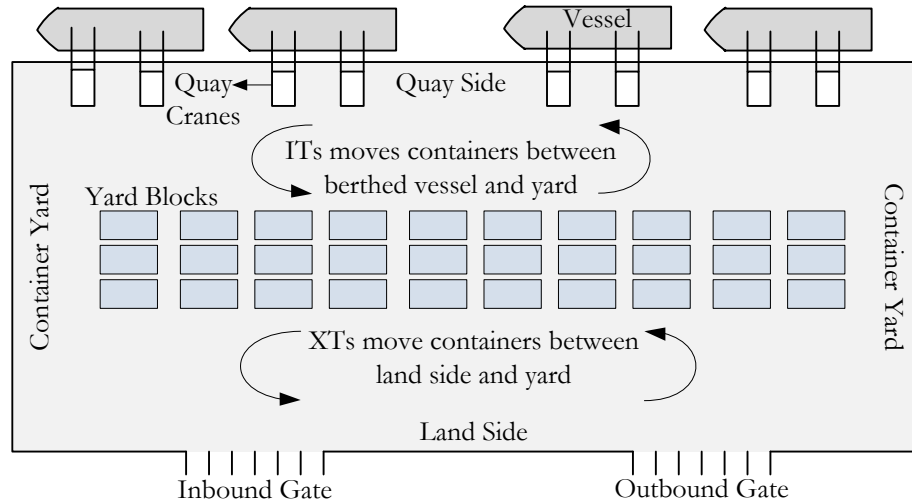

Figure 5.1   A schematic diagram of container terminal

In this paper, we study the storage space allocation problem in a container terminal yard. The yard typically has a fixed storage capacity which is determined at the design stage and is considered a strategic level decision. In this study, we address the daily operational issue which involves assigning yard blocks for newly arriving export and import containers. This problem is considered critical because it relates to the operational efficiency of all the resources in a terminal, including quay cranes, yard cranes, storage space, and internal trucks (Zhang et al., 2003). There are two competing objectives that need to be accounted for when assigning containers to yard blocks. The first objective is to distribute the arriving export and import containers among blocks such that workload imbalance from block to block is reduced; 'workload imbalance' measures the variability of number of containers among blocks at some time (we used standard deviation for this measure). The second objective is to minimize the distance traveled by the ITs between the berth and yard during loading and unloading of containers onto/from the vessel. The

SSAP can be studied at two levels: the 'block level' and 'stack level'. 'Block level' decision finds the block to store a container with the aim of balancing workload among yard blocks and minimizing travel distance of ITs. 'Stack level' decision finds the exact stack in a block to store a container with the aim of minimizing future reshuffling. Our model makes decision at the 'block level'.

There are several important reasons why it is desirable to balance workload among yard blocks. The workload imbalance forces terminal operators to relocate yard cranes among blocks to those with higher workloads. Such relocations of yard cranes are time consuming, blocks road traffic, and results in loss of time in crane's utilization. Also, yard cranes at various blocks act as parallel servers during vessel loading and unloading operations. The vessel turn time is equal to the maximum processing time of these parallel servers. Thus, balancing the workload of these parallel servers is needed to minimize the vessel turn time (Zhang et al., 2003). In addition, past studies on yard crane deployment have found that balancing workload reduces average container handling time (Zhang et al., 2002). Furthermore, workload balancing reduces congestion on the road network inside the terminal because it distributes the resources and traffic more uniformly throughout the network and thus reduces the chances of bottlenecks forming.

In this study, we model the container terminal as a network graph where the gates, blocks and berths are represented by nodes and the container transport routes among these nodes are represented by links. The containers are transported between gate and berth and undergo storage at block nodes for a storage period. In addition to containers, the network supports a population of simple mobile ant agents and their behavior is inspired after real-world ants. In reality, an individual ant is very simple and unsophisticated in behavior; however, collectively they can perform various useful tasks (such as building nests and locating closest

food sources). The collective intelligence of ants have inspired various useful optimization and control algorithms in computer science (Bonabeau et al., 2000). In our work, we exploit the pheromone laying characteristics of an ant colony to solve the SSAP. The artificial ants in our model travel between gate and berths and deposit simulated pheromones along their paths as a function of traveled distance and congestion experienced at the blocks. When export and import containers are transported between the gate and berth, the choice of yard block is made according to pheromone distribution controlled by ants. The performance of the model is measured by the imbalance number of containers and container transport distance between blocks and berths.

The existing research on SSAP uses traditional centralized optimization techniques (a review is provided in the next section). As mentioned, in this study we adopt an agent-based model. Agent-based modeling is a decentralized and a relatively new research field within the realm of artificial intelligence. Researchers and practitioners in many disciplines, from biology to economics, have developed agent-based models, and the number of applications continues to rise (Bernhardt, 2007). While agent-based modeling and multi-agent systems have been applied in many different disciplines, they are relatively unexplored in the area of port operations. In general, the advantages of adopting an agent-based approach over classical optimization are the capability of solving problems of large sizes, producing a time efficient solution, and obtaining a solution adaptive to changes in a dynamic system (Davidsson et al., 2003). There has been no study using a decentralized approach to solve the SSAP. The major distinguishing feature of our distributed ant-based control is that we can solve the allocation problem in real time. In reality, when containers are brought to the terminal or picked up by XTs, their arrivals are not known with certainty. Studies that used traditional optimization techniques use estimates based on historical data for this purpose. In

contrast, our model does not require export/import container arrival information. Also, because of the multi-objective nature of the SSAP the existing literature adopts a hierarchical approach where minimizing workload imbalance and travel distance of ITs are separated and solved in a sequential order. Our approach solves both problems simultaneously. Another advantage of our agent-based approach is that our model can be integrated into a system of agent-based models. Our long term goal is to develop a comprehensive and integrated model (made up of various sub-models) of terminal operations in order to address the operational challenges in a holistic manner. In past work, we have developed agent-based models addressing gate operations (Sharif et al., 2011), real-time yard crane scheduling (Huynh and Vidal, 2010) and inter-block deployment of yard cranes (Sharif et al., 2012).

5.2 Review of Related Studies

There is a large amount of literature available in the area of marine container terminal modeling. The container terminal operations have been receiving greater attention and importance in past years and the number of publications in this area has been growing as well. A survey of container terminals related research can be found in several references: Vis and de Koster (2003); Steenken et al. (2004); Stahlbock and VoB (2008); Crainic and Kim (2007); Murty et al. (2005); Rashidi and Tsang (2006); Vacca et al. (2007); Henesey (2006). A comprehensive review is beyond the scope of this paper and is not provided here.

Research focusing on yard operations generally involves two classes of problems. The first is the SSAP, and the second is the yard crane scheduling problem (YCSP). This section reviews literature related to the former topic. Note that this problem is closely associated with the routing problem of internal transport vehicles (Internal trucks / Automated guided vehicles / Straddle carriers). Thus, some

researchers have studied the SSAP in conjunction with the IT transport routing problem.

The most notable work on the SSAP is by Zhang et al. (2003). They decomposed the problem into two levels and each level is formulated as a mathematical programming model. At the first level, the total number of containers to be placed in each storage block is set to balance workloads among blocks. The second level determines the number of containers associated with each vessel, that constitutes the total number of containers, to put in each block in each period. The objective is to minimize the imbalance of workloads among yard blocks and the total distance to transport the containers between their storage blocks and the vessel berthing locations. The model is solved using a rolling horizon approach.

Murty et al. (2005) proposed a decision support system to address a variety of interrelated decisions in container terminal operation. One of the problems they considered is efficient utilization of storage space while minimizing congestion at blocks and on the roads inside the terminal.

Lee et al. (2007) studied the SSAP in a transshipment hub to efficiently transport containers between the vessels and the storage area so that container reshuffling and traffic congestion is minimized. To reduce reshuffling, unloaded containers are grouped according to their destination vessel. To reduce traffic congestion, a workload balancing protocol was proposed. Two heuristics were developed. The first is a sequential method while the second is a column generation method. Han et al. (2008) extended this work to determine the locations to store the incoming containers.

Bazzazi et al. (2009) used genetic algorithm to solve the SSAP. They extended the problem to consider different types of containers in the allocation decision such as loaded, empty, and refrigerated containers.

As mentioned previously, our approach is unlike the existing studies in the

literature, which used centralized optimization techniques. Our decentralized model is the first study of its kind to have been applied for solving the SSAP. Our distributed ant-based control falls under ant-based algorithms and ant colony optimizations (ACOs) that have been used by researchers in various disciplines to solve complex routing problems in networks. Also, some studies have used ACO for load balancing in such networks. A comprehensive survey of research in ACO can be found in Sim and Sun (2003). Our study is inspired by the work of Schoonderwoerd et al. (1997) who developed an ant-based control for load balancing in telecommunication networks. We assume a similar basic pheromone laying behavior of ants; however, since telecommunication and container terminal networks are different in arrangement and operations we had to make many changes to Schoonderwoerd et al.'s model to account for these differences.

The contributions of this study to the literature are that it provides 1) an agent-based framework for solving the SSAP, including suitable parameters, 2) an approach that effectively and synchronously minimizes the workload imbalance and container transport distance, 3) a relatively simple but adaptive framework that solves the SSAP in real-time, and 4) an approach which is uninfluenced by inaccurate/uncertain container arrival information.

5.3 Methodology

In our model, we build an undirected graph where the terminal gates, blocks and berths are represented as nodes. The links between a pair of nodes are bi-directional and represents the container transport routes. To consider all possible routes, both the terminal gates and berths are linked with all yard blocks. Therefore, if the number of gates is N_{gates}, number of blocks is N_{blocks} and number of berths is N_{berths}, then the network is composed of $(N_{gates} + N_{blocks} + N_{berths})$ nodes and $N_{blocks}(N_{gates} + N_{berths})$ links. Let the set of gates, blocks and berths be denoted

by G, B and V, respectively. Each block $b \in B$ has a container storage capacity c_b and the allowable density of containers for the block is η_b. Then the number of containers stored in a block cannot exceed $(\eta_b \times c_b)$. Let at some time t the number of containers stored in a block is n_b^t, then the block has a spare capacity s_b^t at time t equal to $(\eta_b \times c_b - n_b^t)$. Also, let us assume we have an artificial ant population A in our model. Each ant $a \in A$ has the following variables: age a^{age}, origin node a^{origin}, destination node $a^{destination}$, and $a^{origin} \in G \, or \, V$ and $a^{destination} \in G \, or \, V$. Let the set of containers be denoted as C and each container $c \in C$ has the following variables: origin node c^{origin}, destination node $c^{destination}$, and $c^{origin} \in G \, or \, V$ and $c^{destination} \in V \, or \, G$ for export and import containers.

Pheromone Table and Updating

The artificial ant population in our container terminal network travel between gates and berths just like inbound and outbound containers. For routing of ants we use a table of probabilities at each node known as 'pheromone tables'. For example, a gate node has pheromone tables for every possible destination berths and each table has an entry for every neighbor node (i.e. yard block). A similar table exists for each block and berth nodes. The probabilities in each table correspond to intensity of pheromones laid by ants. These probabilities are used to guide ants and containers in choosing the next node on their path to the destination. The ants lay pheromones as they travel to reinforce their chosen path and the reinforcing mechanism is captured by updating the probabilities accordingly.

For the purpose of illustration, we show in Figure 5.2 a container terminal with one gate, two blocks and one berth. The pheromone table for Gate 1 in this simple configuration is shown in Table 5.1. The probabilities in this table indicate that an ant traveling from Gate 1 to Berth 1 has a 0.65 probability of choosing block1 as the next node and 0.35 probability of choosing Block 2 as the next node. Once an
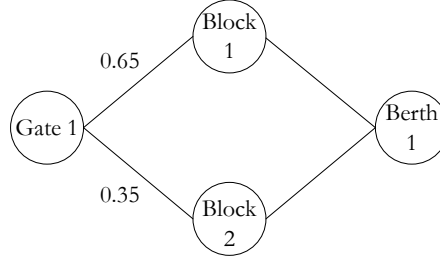
Figure 5.2   An illustration of ants in a network

Table 5.1   The pheromone table for Gate 1

Destination Nodes	Neighbor nodes			
	Block 1	Block 2	Block 3	...
Berth 1	0.65	0.35	...	...
Berth 2	...	...	...	...
...	...	...	...	...

ant arrives at a new node, it updates the pheromone table for that node. Only the entry that corresponds to the origin node of the ant is updated. For example, in Figure 5.2, if an ant originating at Gate 1 with destination Berth 1 has just traveled from Block 2 to Berth 1, it will update the entry corresponding to Gate 1 (the origin) in the pheromone table of Berth 1. The update consists of increasing the probability of choosing Block 2 for ants at Berth 1 wanting to go to Gate 1. In this way, the ants starting from Gate 1 influence the route of the ants for which Gate 1 is the destination. In other words, ants traveling in the outbound direction directly influence the path of ants traveling in the inbound direction, and vice versa. This approach is dissimilar to bi-directional trail laying ants, since pheromones laid from ants traveling in one direction directly influence ants traveling in opposite direction only, not both directions. However, since ants traveling from gate to berths (outbound ants) has a direct impact on the ants traveling from berths to gate (inbound ants), and consequently the inbound ants, in turn, have a direct impact on the route of outbound ants. That is, ants traveling in any direction indirectly influence the route choice of subsequent ants traveling in the same direction by

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directly influencing the route choice of ants traveling in the opposite direction. So, this mechanism is analogous to biological bidirectional pheromone trails, but achieved through a secondary form of interaction.

Formally, the table of probabilities for routing (i.e. the pheromone tables) of a gate node is PT_g and has N_{berths} entries. The pheromone table of a block node is PT_b and has $(N_{gates} + N_{berths})$ entries. The pheromone table of a berth node is PT_v and has N_{gates} entries. Each entry corresponds to a destination (a gate for import containers and a berth for export containers) and represents the probability of selecting the next node on the route (i.e. the block) to the destination node. Upon arrival at a node, the probabilities in the pheromone table for the origin node of an ant are updated. The entry corresponding to the node the ant just moved from will be increased using the following formula.

$$p_{new} = \frac{p_{old} + \delta p}{1 + \delta p}, \text{where } \delta p \text{ is the amount of increase in probability (or pheromone).}$$

The remaining entries will be decreased using the following formula.

$$p_{new} = \frac{p_{old}}{1 + \delta p}$$

Note that the probabilities are altered in such a manner that their sum will always remain 1 and can be construed as probabilities. Using this approach of normalization, the gain in probability is much higher for initially small probabilities compared to those which are initially greater, for a given δp. Likewise, the reduction is more rapid for higher old probabilities compared to smaller old probabilities. Since the small probabilities (indicating an unpopular route) can rise more rapidly (becoming a preferred route), this can alleviate the 'shortcut problem' which is discussed later.

Shortest path and workload balancing

This section describes how ants find shorter paths in the network and avoid block nodes which are congested. To find shorter paths we assume that each ant has an age variable a^{age} which increases proportionally with the distance the ant travels. In contrast, the δp used by an ant to update the probabilities gradually decreases with age. In this manner an ant taking a longer path will have relatively higher age and lower δp. Thus, the influence on route selection probabilities will be less significant and the model will increasingly favor the ants taking shorter paths. For the other objective of avoiding congested blocks, we adopt two mechanisms. First, it is assumed that the ants are delayed (put on hold) at blocks and the time period of delay is a function of degree of congestion at the block. That is, the higher the congestion, the longer an ant is held at the block before moving on to the next node. Second, the age of an ant is increased by the amount of time it is held at the node. Thus, the second mechanism uses the information from the first mechanism. The role of the first mechanism is to temporarily reduce the number of ants flowing out of a congested node, thus preventing the ants from updating the pheromone table and decrease their influence on other ants to be routed towards the congested node. This allows some time for the alternate paths to emerge. The role of the second mechanism is to increase the age of ants by the duration of delay. Thus, δp will be smaller and consequently the impact on the pheromone table will be less. Therefore, both of these mechanisms have the same objective, to discourage the routes involving congested blocks. While one can simply use the latter mechanism for this objective, incorporating the first mechanism is desirable because it uses delay as a function of the level of congestion and it can be used to regulate the relative weighting between shortest path and least congested route. The updating of probabilities as described in the previous section is a function of age. Age and

δp of an ant is determined by the following formulas.

$$a^{age} = Distance\ traveled\ by\ the\ ant\ +\ Delay\ at\ a\ congested\ node$$

Delay is a function of spare capacity of the block nodes given by the formula below.

$$delay = k_3\ \times\ exp(k_4 \times s_b^t)$$

where k_1, k_2, k_3 and k_4 are numeric constants. Figure 5.3 shows a sample plot of how the update probability may be changed with age of ant. Figure 5.4 shows a plot illustrating the relationship between delay at a block and its spare capacity.

The chart contains the following equation and constants:

$$\delta p^a = \frac{k_1}{a^{age} - a_{max}^{age} + a_{min}^{age}} + k_2$$

$$k_1 = 2.5 \qquad k_2 = 0.005$$

$$a_{max}^{age} = 750 \qquad a_{min}^{age} = 400$$
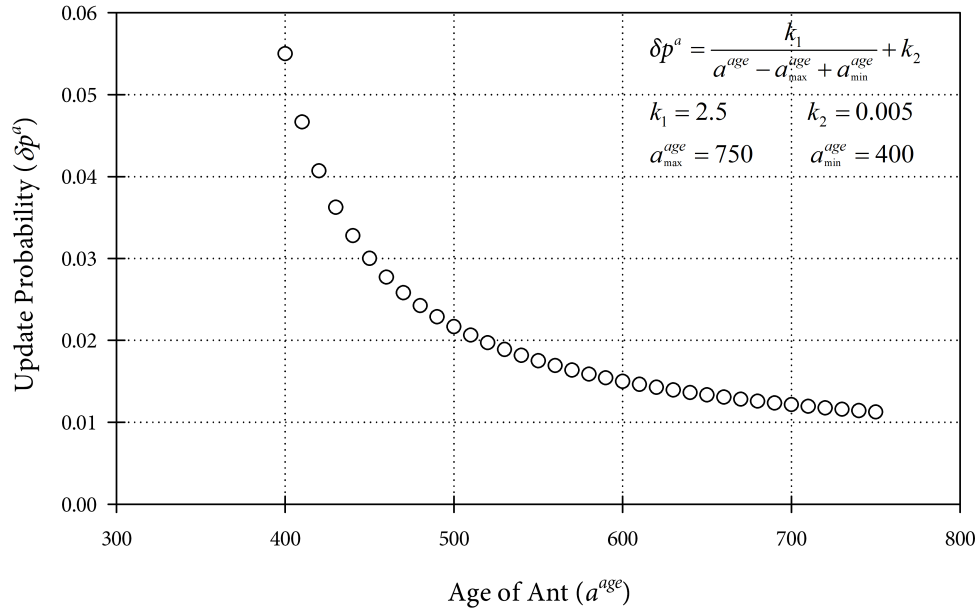
Figure 5.3   Relationship between update probability and age of ants

Routing of Container and Ant Traffic

The routing of export and import containers takes place independently of routing of ants. The following list explains how arrivals of containers are generated and containers are routed in the network.

1. Export containers are generated from the terminal gates using random Poisson arrival with a mean of λ_g per time-unit.
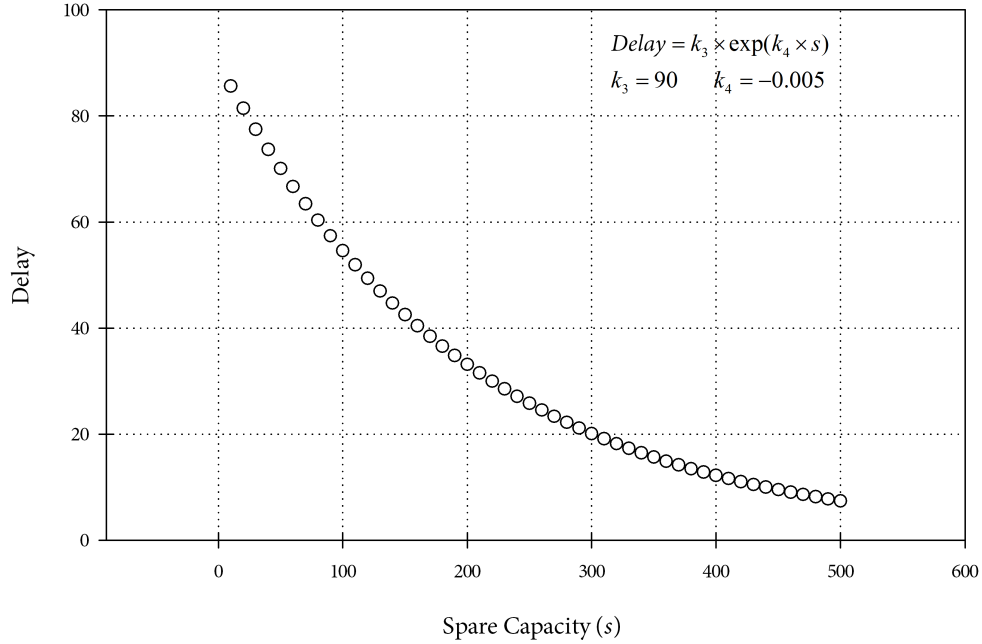
Figure 5.4   Relationship between delay time and spare capacity of a block

2. Each export container generated at the gate is assigned a random berth as destination.

3. Import containers are generated from each berth using random Poisson arrival with a mean of λ_v per time-unit.

4. Each import container generated at a berth is assigned the terminal gate as destination.

5. The storage period/dwell time of containers at a block follows random exponential distribution with a mean of μ time-units.

6. Each import container at berth and export container at the gate selects a block according to the maximum probability in the pheromone table. However, if the block has already reached its capacity, the path will be revised based on the next largest probability and so on.

The following list explains how ants are generated and routed in the network.

1. The ants are generated from every terminal gate node at a constant rate of αN_{berths} ants per time-unit.

2. Each ant generated at the gate is assigned a random berth as destination.

3. The ants are generated from every berth node using at a constant rate of αN_{gates} ants per time-unit

4. Each ant generated at a berth is assigned a terminal gate as destination.

5. It takes (distance/speed) time steps for an ant to move between two nodes.

The dynamic interaction between ants and containers is illustrated in Figure 5.5. Newly arriving export and import containers creates demand on blocks and reduce the available capacity. Thus, arrivals of new containers impact the route of ants via the delay mechanism. The ants influence the pheromone tables via probability updating which in turn determine the routing of subsequent containers. Also, as ants update the pheromone tables, they influence the route of the subsequent ants.
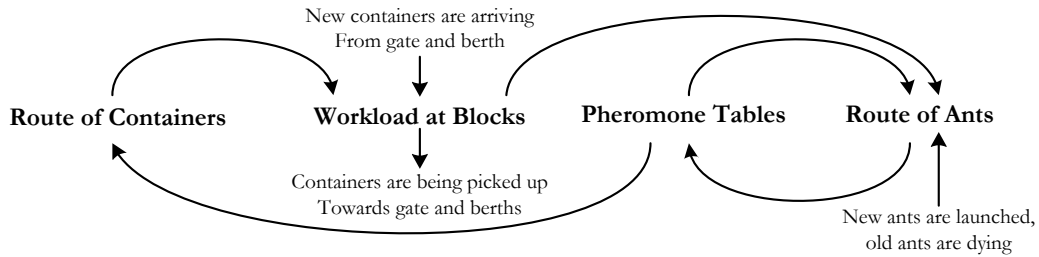
Figure 5.5   Influence between container routes, workload at blocks, pheromone tables and route of ants. The arrow represents direction of influence.

Noise

Another parameter that may be included in the model is 'noise' or exploration probability. A noise factor s implies that when an ant determines the next node in the path, there is a probability s that the ant will choose an entirely random

next node and a probability of $(1 - s)$ that the next node is selected based on the pheromone table. Two well-known problems associated with ant-based routing are 'Blocking problem' and 'Shortcut Problem'. Blocking problem arise when a current well-travelled path becomes congested or unavailable. In such cases, it may take the ants a long time to find and switch to a new path. Shortcut problem arise when a new shorter route becomes available, but the ants continue to take the previously chosen path because the strong trail strengths of those paths. For more information on the shortcut problem and the blocking problem see Sutton (1991). One way to alleviate the 'shortcut problem' and 'blocking problem' is to incorporate the noise factor. The noise is intended to avoid 'freezing' of paths by making the ants occasionally travel in even ineffective routes and as a result keep some information about the network on the model (Schoonderwoerd et al., 1997). Our model uses a noise factor of 1%.

Initial Conditions

Initially the pheromone tables can be populated with random or equal probability entries. It is also possible to choose probabilities based on available information about the terminal network layout. However, for this ant-based framework, providing this initial information of network layout is not required. If the demand is almost zero (i.e. without any container traffic), there will be no congestion and the ants will find the shortest path based on the distances among nodes. The method in which ants find the shortest paths can be understood as follows. First, the ant that is first to reach the destination (i.e. taking the shortest route) will start to influence the path of newly generated ants before others. Second, shorter paths mean a higher number of ants will complete these paths in a given time and the pheromone intensity will rise faster. Third, the ants taking shorter paths have less age therefore their degree of influence on pheromone tables is greater.

Initially, we allow some time for the ants to find the shortest routes in the network. Then we start to generate containers and they create workload on blocks. Ants will then start to adapt their routes based on congestion at blocks. We initialize the pheromone tables with equal probabilities of choosing among blocks and then let the model run for a fixed period with ant traffic only before generating containers.

5.4 MODEL IMPLEMENTATION

The aforementioned methodologies were implemented in Netlogo, a multi-agent simulation framework (Wilensky 1999). Netlogo facilitates experimentation and evaluation of the proposed method. It provides many useful primitives (i.e. procedural commands) that expedite model implementation. In our framework, the gate, blocks and berths are modeled as stationary agents and containers and ants are modeled as mobile agents. Figure 5.6 shows a screenshot of our model's graphical user interface (GUI). As shown, the model provides several sliders to allow for changing of various parameter values. The parameters that could be changed directly on the GUI include the number of gates, blocks and berths, mean export and import containers arrival rate, and mean ant generation rate. The GUI also provides input panels for changing the capacity of yard blocks, mean dwell time of containers, length of initialization period, noise factor, etc.

The implementation consists of two main procedures. The 'setup procedure' is executed once at the beginning of each model run and the 'go procedure' is executed in a loop at every time-step.

Setup Procedure

Setup the layout of the terminal network including gates, blocks and berths
Setup the global and local variables

103
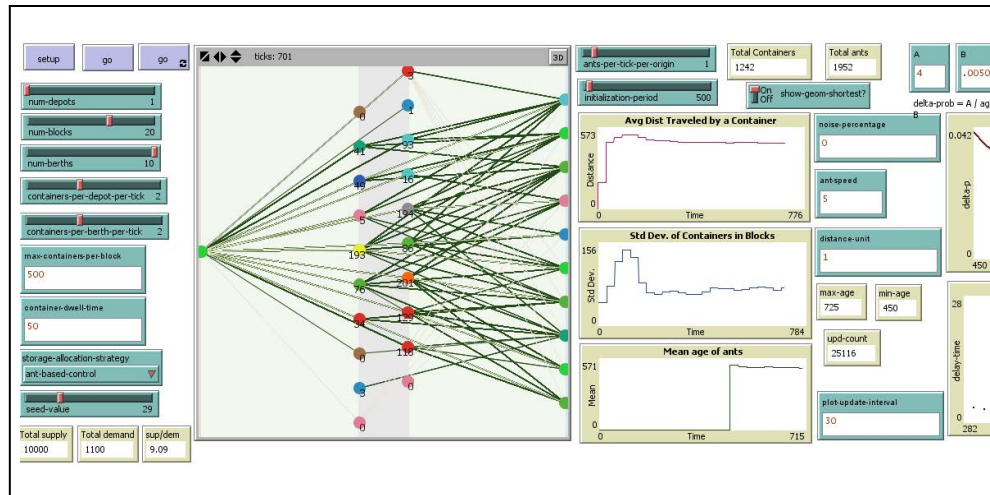
Figure 5.6   A screenshot of the agent-based model.

Setup initial state of containers storage at blocks

Go Procedure

Increment time step by 1

Call 'ants procedure'

Call 'container procedure'

Update graphics, plots and results

Ants Procedure

Generate outbound ants from gates toward random berths

Generate inbound ants from berths toward random gates

Select next node for ants either randomly or probabilistically (based on noise factor)

Determine ants travel time to next node (based on geometric distance and ant speed)

Increase age of ants at a rate proportional to their travel time

Hold ants at blocks for the delay period determined from available capacity of the block

Increase age of ants by delay period

Update the relevant pheromone table once an ant arrive at a new node

Make ants die when they arrive at their destination nodes

Containers Procedure

Generate export containers from gates with destination toward random berths

Generate import containers from berths with destination toward random gates

Select block for containers according to maximum probability in relevant pheromone
table

Put containers on hold at blocks for the storage period

Move containers to destination node when storage period expires

5.5 EXPERIMENTAL DESIGN AND RESULTS

We tested our approach on a hypothetical container terminal. The test parameters
that were used for the experiments are shown in Table 5.2. These parameters
can be divided into two categories. The first set of parameters describes the
characteristics of the terminal and container generation rate while second set of
parameters describes the parameters related to ant-based control. As evident
from Table 5.2, the size of the container terminal we have modeled is comparable
to a fairly large real world terminal. There is a constant average demand of
2,500 containers on the network while the total yard capacity is 10,000 containers.
An estimate of the average total number of containers in the system can be
found by $\mu(N_{gates} \times \lambda_g + N_{berths} \times \lambda_v)$, which is the average total demand in the
system. The average supply can be found by $N_{blocks}(\eta_b \times c_b)$. Thus, the supply-
demand ratio can be estimated to be $(N_{blocks}(\eta_b \times c_b))/(\mu(N_{gates} \times \lambda_g + N_{berths} \times \lambda_v))$. Similarly export and import containers ratio in the system is given by

$(N_{gates} \times \lambda_g)/(N_{berths} \times \lambda_v)$. These formulas are used to compute the relevant parameters in Table 5.2. The performance measures recorded from our model were 1) average container transport distance, and 2) average standard deviation of number of containers among blocks, which are measured periodically. The experiments were conducted on a personal computer with 2.57 GHz Centrino dual-core CPU and 4 Gigabytes of RAM.

Table 5.2   Parameters and their values used in the model.

Parameter	Value	Unit
Container terminal parameters		
Number of gates (N_{gates})	1	Nos
Number of blocks (N_{blocks})	20	Nos
Number of berths (N_{berths})	5	Nos
Mean container arrival per gate per time-unit (λ_g)	25	Nos
Mean container arrival per berth per time-unit (λ_v)	5	Nos
Mean dwell time of containers (μ)	50 (min 5)	Time units
Storage capacity per block ($\eta_b \times c_b$)	500	Nos
Supply-Demand ratio	4	-
Export-Import containers ratio	1	-
Ant related parameters		
Ant launch rate per gate per time-unit (αN_{berths})	5	Nos
Ant launch rate per berth per time-unit (αN_{gates})	1	Nos
Ant speed	5	Distance/time-unit
Ant age increase rate	5	Per time-unit
Update probability equation coefficients	$k_1 = 4.5, k_2 = 0.005$	-
Delay equation coefficients	$k_3 = 90, k_4 = -0.005$	-
Initialization period	3000	Time units
Noise factor (s)	1%	-

Figure 5.7 shows the convergence characteristics of average container transport distance in the network for two cases: 1) containers are routed based on shortest
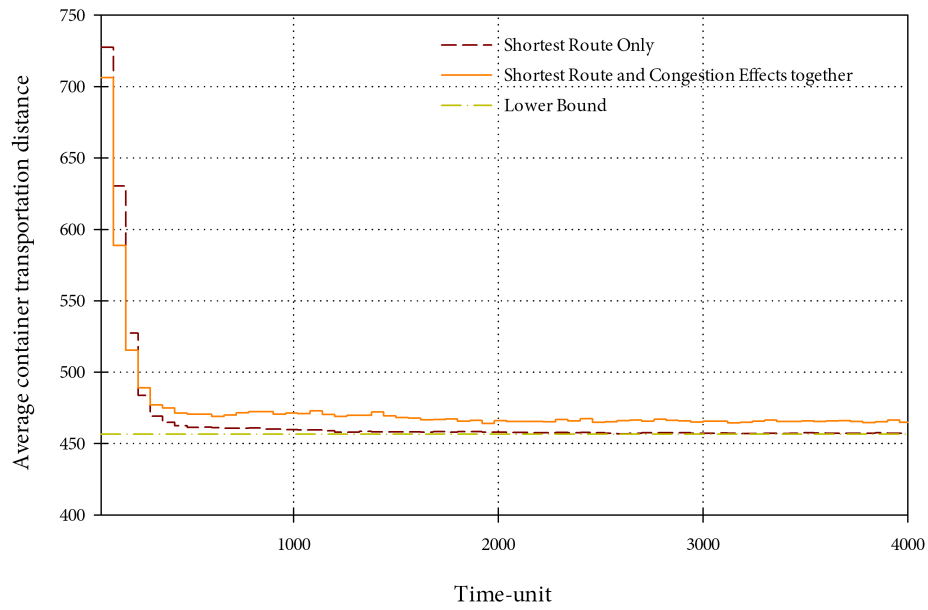
Figure 5.7   Convergence of container transport cost over time
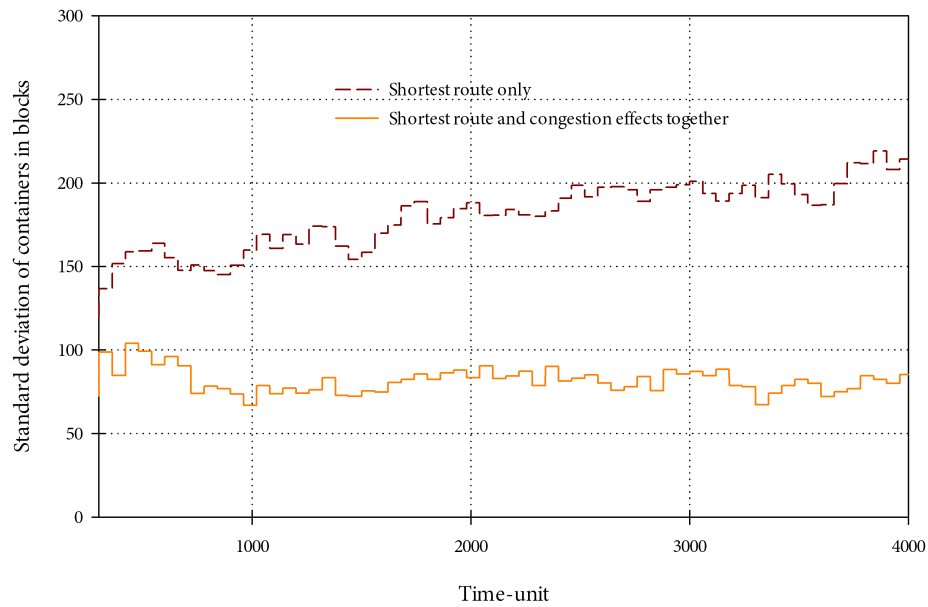
Figure 5.8   Standard deviation of containers in blocks

distance only without considering congestion, and 2) containers are routed based on considering both shortest distance and congestion. It also shows the lower bound of the average transport distance which can be found assuming every container take their shortest route in the network. It can be seen that convergence occurs around 500 time-units. The average age of ants after reaching their destination will also follow similar convergence characteristics. The *lower bound* for ants can be determined by assuming each ant is taking the shortest route in the network to destination. However, the progression of convergence for containers will be faster than ants. This is because containers use maximum probability for selecting a route. That is, it occurs as soon as a large fraction of ants starts to dominate the shortest path. Since ants take probabilistic path their convergence do not occur until (almost) all of them select the shortest paths. Figure 5.7 can be used to determine an appropriate initialization period. For example, for this particular scenario it is desirable to begin routing containers using pheromone table after 500 time-units to minimize the transport distance. Figure 5.7 also shows that when transport distance is the only consideration (no congestion in network) the transport distance converges to the lower bound (456). When container demands are high we have to also consider the limited capacity of yard blocks and impacts of congestion. When congestion effect and capacity effect are added to the model, the average transport distance converges to 466 (2% above the lower bound).

Figure 5.8 shows standard deviation of number of containers among blocks over time for two cases: 1) containers are routed based on shortest distance only without considering congestion, and 2) containers are routed based on considering both shortest distance and congestion.. We used standard deviation as a performance measure of our workload balance mechanism. In absence of congestion, the routing of containers gravitates toward shorter distances over time and therefore the standard deviation steadily rises (the top plot in Figure 5.8). With congestion

and capacity effects added to the model the standard deviation falls to a lower value (approx. 80). This is because arriving containers are more distributed among blocks. Also, note that the standard deviation in this case remains generally steady over time. Based on the combined effect of shortest distance and congestion the model finds and maintains an appropriate distribution of containers in the network to accommodate both objectives. In other words, the containers take first/second/third/... best paths proportionally to avoid congestion while keeping the transport distances minimal.

We have also varied the parameters in Table 5.2 to examine their impact on the performance of our ant-based control model. The first three parameters N_{gates}, N_{blocks} and N_{berths} determine the capacity of network and number of possible routes for containers and ants. Smaller number of routes indicates that convergence will occur faster than larger number of routes for a given ant generation rate. λ_g, λ_v, μ, $\eta_b \times c_b$ determine the number of containers in the network and therefore the probability of reaching capacity of block and degree of congestion These parameters do not have any influence on the performance of ant-based control. The last two parameters, supply-demand ratio and export-import ratio, are based on earlier parameters. The second set of parameters in Table 5.2 are ant-related parameters. The higher the number of αN_{berths} and αN_{gates} the faster the model achieve convergence; however, these parameters together with 'ant speed' determines the number of artificial ants on network and a very large number of ants will increase the computation time of the model. The parameter 'age increase rate' has no influence on the model speed or convergence. The chosen values of the coefficients k_1, k_2, k_3 and k_4 appear to be working particularly well for the scenarios we tested. As long as k_1 and k_2 defines a decreasing function the ants will find the shortest path, but the time required for convergence will vary. Similarly k_3 and k_4 determine the relative importance of load balancing; however,

using very high values indicate long delays which will increase the computation time of the model.

5.6 Conclusion

This paper addressed the storage space allocation problem (SSAP) in a marine container terminal using ant-based control. Our approach implements a distributed allocation and assigns containers to blocks dynamically as they arrive at the gate or berth. Our approach solves the problem in real-time without requiring advanced container arrival information. It differs from existing approaches which uses the centralized control method and hence require container arrival information. Our model considered two competing objectives when assigning storage blocks to containers. The first objective is to distribute the arriving containers among blocks such that workload imbalance from block to block is reduced. The second objective is to assign the blocks to containers such that the distance traveled by internal transport vehicles are minimized during the loading and unloading of the vessel. Simulation results showed that the proposed approach effectively balances the workload among yard blocks and thus minimizes congestion on the road network for trucks and yard cranes. At the same time, the transport distance of containers between yard blocks and berth is minimized. In future research, we plan to investigate the suitability of the ant-based control method to solve the SSAP at the stack level to minimize container rehandling.

Chapter 6

Conclusion

In this dissertation, three completed research studies are presented that address some critical problems in container terminal operations. Specifically, the dissertation investigates the applicability of agent-based models for the 'terminal gate congestion problem', 'interblock yard crane scheduling problem', and 'storage space allocation problem'. The research studies undertaken in this dissertation are significant for several reasons. First, efficient solutions to these problems are critical as they contribute to improved terminal productivity and competitiveness. Second, these problems have been identified as bottlenecks in terminal and drayage operations. Third, these problems are not isolated, independent processes but they impact efficiency of other related operations in the terminal indirectly. Fourth, these problems present growing environmental concerns in urban areas because of emission from trucks.

In the first study involving gate congestion problem, an agent-based framework was proposed for the truck dispatchers to avoid long queues at marine terminal gates. The major research question was: can the proposed agent-based paradigm provide steady truck arrivals at terminal gates to reduce the trucks' average waiting time? To answer this question, a formulation was adapted from the El Farol Bar Problem and subsequently implemented via simulation. The proposed model employs real-time gate congestion information obtained from

gate webcams and some simple logics for estimating the expected truck wait time. The implementation contains a handful of parameters that attempts to capture different variables relevant to the gate congestion problem. Next, extensive experiments were conducted by choosing practical ranges of the parameters. Results demonstrate that truck depots can manage (without any collaboration with one another) to minimize congestion and emissions by using the proposed model. The findings also reveal how the selection of parameters impact the average and maximum wait time of trucks, as well as how depots can benefit from extended operational hours.

In the second study involving interblock yard crane scheduling problem, an agent-based approach was presented to assign and relocate yard cranes among yard blocks based on the forecasted work volumes. Most container terminals use yard cranes to transfer containers between the yard and trucks (both external and internal). Given varying work volumes among yard blocks with different planning periods an efficient work schedule for yard cranes is necessary. The objective of this study is to reduce the work volume that remains incomplete at the end of a planning period. Several preference functions are offered for yard cranes and blocks which are modeled as agents. These preference functions are designed to find effective schedules for yard cranes. In addition, various rules for the initial assignment of yard cranes to blocks are examined. The analysis demonstrated that the model can effectively and efficiently reduce the percentage of incomplete work volume for any real-world sized problem.

In the third study a novel solution approach is presented for storage space allocation problem (SSAP). SSAP is the assignment of arriving containers to yard blocks in a container terminal. The container terminal is modeled as a network of gates, yard blocks and berths on which export and import containers are considered as bi-directional traffic. Utilizing an ant-based control method the model

determines the route for each individual container based on two competing objectives: 1) balance the workload among yard blocks, and 2) minimize the distance traveled by internal trucks between yard blocks and berths. The model exploits the trail laying behavior of ant colonies where ants deposit pheromones as a function of traveled distance and congestion at the blocks. The route of a container (i.e. selection of a yard block) is based on the pheromone distribution on the network. The results from experiments show that the proposed approach is effective in balancing the workload among yard blocks and reducing the distance traveled by internal transport vehicles during vessel loading and unloading operations.

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