Application of DEA to the analysis of AGV fleet operations in a port container terminal

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Abstract

This paper presents a decision making approach based on Data Envelopment Analysis (DEA) for determining an efficient container handling strategy at an automated port container terminal. Containers are unloaded from the ship by quay cranes and transported to the storage area by Automated Guided Vehicles (AGVs). The objective of this paper is to show how dispatching rules and a number of employed AGVs affect measures of effectiveness of container handling process and to compare their efficiencies using DEA. It was shown that simulation modeling and efficiency evaluation of AGV fleet operations can be useful for the planning purpose.

Keywords: AGV, Port Container Terminal, Simulation, Data Envelopment Analysis

1. Introduction

Port container terminal provides a service of container handling, more precisely, unloading containers from ships onto inland vehicles (typically trucks and trains), and vice versa, with the purpose of distributing containers to the end users. Terminals are equipped with corresponding reloading machinery and with opened storage areas dedicated for shorter or longer storage of loaded or empty containers. In the process of planning the container handling at port container terminals, arrivals of container ships cannot be precisely defined in time and they represent a group of approximately known values. One of the ways to improve the total productivity of a container terminal (to reduce ship turnaround times) is to increase the automation of the cargo handling and transport, and to use the most efficient container handling scenario. Advantages in the fields of electronic, automation, information technologies and sensors are enabling a development of fully automated container terminals. In the studied container terminal (Ioannou et al. 2000), the quay cranes were unloading containers from the ship; the containers were further transported to the storage areas by automated guided vehicles (AGVs).

The objective of this paper was to show how dispatching rules and a number of employed AGVs affect different measures of effectiveness (MOEs) of container handling (number of containers in queue, AGV utilization, etc), and
to compare their efficiencies using Data Envelopment Analysis (DEA). Most often, analytical methods are used to solve fleet sizing problems, which are justified in deterministic context. In this study, due to presence of uncertainties in ship arrivals and container handling operations, stochastic variables were used and a simulation model was developed. The simulation model was developed and tested in the academic version of the simulation package Arena (Kelton, 2004). Following dispatching rules of AGVs at container terminal were used: “cyclic”, “random”, the “smallest distance”, and the “largest distance”. Dispatching rules were assessed using different efficiency criteria, such as maximizing system efficiency, minimizing queue length and maximizing vehicle utilization. Simulation experiments showed the differences in the number of containers that were transferred and the differences in the queue length at Berth; however, there was no substantial difference in the AGV utilization. For that reason, DEA method was used to rank the competitive dispatching rules, taking into account number of employed AGVs, number of containers in the queue waiting to be served by AGVs, AGV utilization, and number of containers that were transferred to the storage areas. To the best of our knowledge, the analysis of AGV fleet operations has not been previously done using DEA for efficiency evaluation. It was shown that DEA method is useful to test the container handling scenarios and determine an efficient one for the planning purpose.

2. Theoretical Background

2.1. Automated Port Container Terminals and Route Planning for the Automated Guided Vehicles

Major modern ports, due to the increase in demand, are considering various concepts and possible solutions that might enable increase in the terminal productivity without major investments in new land and port expansion. The increase in the number of containers, also, demands more efficient cargo handling process in order to maintain high productivity. Automated systems of cargo handling are able to meet the demands of the port, in terms of productivity, as well as in terms of decreasing costs and minimizing terminal expansion.

Automated port container terminal that uses AGVs is a conventional container terminal with an exception of using AGVs for container transport instead of manual transport equipment. The future of AGVs is in the full automation of their control, which will enable them to perform the tasks that currently require significant work force. AGVs are becoming more popular in flexible manufacturing systems, and in the systems for container handling (Liu et al., 2004).

Detailed time-savings and cost analysis (ship waiting time, unloading/loading times, etc) is required to determine the amount of container traffic that justifies the usage of AGVs in the process of container transfer. If higher number of AGVs are used on container terminal, efficient planning and choice of optimal routes is necessary to optimally connect all elements in the system. A route planning for the AGVs consists of choosing the number of vehicles and determining the optimal route for their movement. Vehicle choice and its appropriate usage are important part of terminal design. The task of guiding and controlling the vehicle during its movement is very complex within the AGV systems. The process of controlling the AGVs consists of a number of components, such as sending a vehicle to the certain position, choosing appropriate route for the vehicle movement, and sending a vehicle in a timely manner.

2.2. Dispatching Rules for Automated Guided Vehicles within a Container Terminal

AGVs dispatching rules within a container terminal is a separate topic that has been studied in depth. Tunchoco and Egbelu (1984) are one of the pioneers in the field of flexible automated systems. The most commonly used dispatching rules for design and operation of automated container terminals are (Tunchoco & Egbelu, 1984; Klein & Kim, 1996):

- Random work-center: From the list of all work-centers that are requesting the service, one work-center is randomly selected, and the vehicle is dispatched to it.
- Shortest travel time/distance: This rule minimizes the percentage of time vehicles travel empty by dispatching the vehicle to the work-center that is closest (in terms of travel time or distance) to that vehicle.
- Very sensitive to the facility layout and position of equipment; it is possible that some work-centers never qualify to receive a vehicle dispatch.
- Longest travel time/distance: The work-center that is farthest away from the vehicle will have the highest priority. Used mostly for system experimentation.
- Maximum outgoing queue size: Vehicle is dispatched to the work-center whose outgoing queue has the highest number of units, not assigned to any vehicle, waiting for the pickup.
- Minimum remaining outgoing queue space: This rule reduces the possibility of blocking work-center by dispatching the vehicle to the work-center that has the minimal difference between outgoing queue capacity and the current length of the queue; also, the number of unassigned unit loads has to be equal or greater to one.
- Modified first come – first serve rule: The basis of this rule is that no work-center can have two or more outstanding requests for the vehicle. The available vehicle is assigned to the work-center with the earliest outstanding request. Afterwards, if there are more units awaiting the vehicle in that work-center, the new request will be assigned the time when the old request has been satisfied.
- Unit Load Shop Arrival Time rule: This rule reduces the time loading units spend in the queue.
- Random vehicle: The task is randomly assigned to any available vehicle.
- Nearest vehicle: Using traveling speed of the vehicles, travel distance between the vehicle demand point and all the available vehicles are calculated. The vehicle with the shortest travel distance is dispatched to the vehicle demand point.
- Farthest vehicle: Opposite to the nearest vehicle rule, this rule dispatches vehicle to the vehicle demand point with the longest travel distance. Provides the idea of what unnecessary vehicle traveling could have on system.
- Longest idle vehicle: The vehicle that was idle for the longest time among all the idle vehicles will be first dispatched to the vehicle demand point. This rule provides workload balance among vehicles.
- Least utilized vehicle: The vehicle whose mean utilization (calculated up to the point of the vehicle demand) is minimal will be dispatched to the vehicle demand point. Also acts as workload balancer among vehicles.

Multiple objectives that are commonly used in the decision making process for the vehicle dispatching task are maximizing vehicle utilization, maximizing throughput, minimizing queue length, and balancing work load.

2.3. Relevant Data Envelopment Analysis Applications

The founders of DEA methodology, Charnes et al. (1978), have suggested a performance measurement approach for calculating the relative efficiencies of entities that are called Decision Making Units, DMUs (Cooper et al., 2004). These units convert multiple inputs into multiple outputs. Multiple inputs \((x_i, i=1,\ldots,m)\) are reduced to a single ‘virtual’ input, and multiple outputs \((y_r, r=1,\ldots,s)\) are reduced to a single ‘virtual’ output using weight factors: \(\nu_i, \mu_r\). Each DMU is allowed to determine its own weights (1) with the objective of maximizing its own efficiency (a weighted sum of outputs divided by a weighted sum of inputs). This problem is defined as a fractional programming model, known as the “CCR-ratio model”, which can be reduced to the linear programming model (Cooper et al., 2005). An additional constraint is introduced (2), setting the denominator of the objective function equal to one. By inequalities (3), the efficiencies of all DMUs are restricted to lie between zero and one (0% and 100%).

The basic DEA model is formulated in the following form:

\[
\begin{align*}
\text{(Max)} \quad h_k(\mu, \nu) &= \sum_{r=1}^{s} \mu_r y_{rk} \\
\sum_{i=1}^{m} \nu_i x_{ik} &= 1 \\
\sum_{r=1}^{s} \mu_r y_{rk} - \sum_{i=1}^{m} \nu_i x_{ik} &\leq 0, \quad k = 1, 2, \ldots, n \\
\mu_r &\geq \varepsilon, \quad r = 1, 2, \ldots, s \\
\nu_i &\geq \varepsilon, \quad i = 1, 2, \ldots, m,
\end{align*}
\]

where:
- \(h_k\) – relative efficiency of \(k\)-th DMU; \(n\) – number of DMUs that should be compared; \(m\) – number of inputs; \(s\) – number of outputs; \(\mu_r\) – weight of the output \(r\); \(\nu_i\) – weight of the input \(i\).

If the value of \(h_k\) in the objective function is equal to 1, then \(k\)-th DMU is relatively efficient. However, if it is less than 1, then DMU\(_k\) is relatively inefficient and the value of \(h_k\) shows the percentage by which DMU should
decrease its inputs. DMU_k can be considered fully efficient, if and only if, the values of other DMUs do not provide the evidence that any of its inputs or outputs could be improved without impairing any other input or output.

One of the drawbacks of the basic DEA models is that they are not capable of ranking the efficient DMUs. For that reason, Anderson and Peterson (1993) had shown how CCR model could be modified to rank efficient DMUs. This model is often referred as super-efficiency model. Basic model modification is done by removing constraint (2) from the problem constraint group. DEA models, modified in this way, allow ranking of the efficient DMUs (in the similar way as inefficient units are ranked) based on the efficiency score that can be greater or equal to one.

The most successful application of DEA methodology was in determining the efficiency performance in many fields, such as: banks, education, medical and social institutions, military, agriculture, economy, etc. During the last few decades, many research papers attempting to evaluate port efficiency using DEA method have been conducted. In recent years, DEA method has been successfully applied to the analysis of port container terminals (Tongzon, 2001; Valentine and Gray, 2001; Wang et al., 2002; Barros, 2003; Barros and Athanassiu, 2004; Cullinane et al., 2004; Min and Park, 2005; Cullinane and Wang, 2006; Kaisar et al.; 2006).

With a purpose of planning dry bulk cargo handling, Pjevič and Vukadinović (2007, 2010) analyzed the inland port terminal capacity and gave proposals for capacity increase. Three different scenarios, varying labor force and loading/unloading equipment, were simulated. MOEs were collected and analyzed. Using simulation results, DEA followed. It enabled efficiency analysis of proposed scenarios, and their sub-scenarios, for dry bulk cargo handling. DEA, also, found its application in the field of analyzing the efficiency of dispatching rules by ranking the dispatching rules and providing a basis for decision making (Braglia and Petroni, 1999; Kuo et al., 2008).

3. The Applied Research Methodology

3.1. Assumptions for the Simulation Model of the Port Container Terminal

Layout and characteristics of the automated container terminal and equipment were determined based on the assumptions from the study by Ioannou et al. (2000) about expected container traffic. This paper only examined handling of import containers that arrive at port by ships, and need to be transferred from Berth to Storage yard, Gate or Train buffer. Figure 1 shows layout of the simulated container terminal.

![Figure 1. Layout of the port container terminal](image-url)

The length of an AGV path is determined by the length and width of the shown terminal layout. AGVs are loaded at Berth and travel to assigned locations to be unloaded. It is assumed that there are 5 yard cranes working at 5 unloading stations within a Storage yard. Gate and Train buffers contain two unloading stations (two yard cranes) each.
Following assumptions were used in the simulation model:
- Ships capable of carrying 2000 TEUs arrive 85% loaded.
- Ship turnaround time is 16 h (during two shifts).
- Three quay cranes are assigned to a ship. Average container crane capacity is assumed to be 36 containers per hour.
- Speeds of empty and full AGVs are 16 km/h and 8 km/h, respectively.
- Time spent unloading of an AGV is 60 seconds within container storage areas. It includes time necessary for crane to pick up and lift the container and time to free the AGV.
- Unloaded containers are distributed as follows: 74% of the total number of containers arrived by ship depart to the Storage yard, 18.5% depart to Train buffer, and 7.5% depart to Gate buffer.

3.2. AGV Control Logic and Traffic Rules

Containers were transferred between Berth and storage areas in three following tasks:

1) Transfer of containers between quay crane and Gate buffer;
2) Transfer of containers between quay crane and Train buffer;
3) Transfer of containers between quay crane and Storage yard.

The AGVs should perform these tasks efficiently without the possibility of collision, conflicts or deadlocks. The terminal could be viewed as a network of intersections with nodes where loading and unloading takes place. Once the pick-up and drop-off points are assigned to a particular AGV, the path is uniquely determined by using the intermediate nodes. A conflict between two or more AGVs may occur during the following situations:

1. AGVs are arriving at an intersection, located between two adjacent nodes, from different path segments at the same time. To resolve this type of conflict, the ‘Modified First Come First Pass’ (MFCFP) protocol can be used (Liu et al., 2004).
2. AGVs are traveling along the same path with different speeds. This could happen when one vehicle is loaded and the other is empty. To prevent this conflict, there are zones in which speed is restricted to the speed of loaded AGV.
3. An AGV stops ahead in the moving direction. The vehicle following distance between two vehicles is set at 14 m, which provides enough room for the second vehicle to stop if the first vehicle stops.

3.3. Simulation Experiments

AGVs were moved using following dispatching rules: “cyclic”, “random”, the “smallest distance”, and the “largest distance”. Additionally, for each dispatching rule, number of employed AGVs was varied: 18, 20, and 23 AGVs. Trial-and-error method was used to determine the observed number of AGVs. This method gave the total of 12 scenarios.

Due to the restriction of the academic version of simulation software Arena, simulation interval was set as a duration of one work day (16 h). Recorded MOEs were:
- Number of served containers (total number of containers that are moved from Berth to all three storage areas);
- Number of containers in the queue (number of containers unloaded from the ship by quay cranes, waiting for AGVs to be transferred to one of the storage areas);
- AGV idle rate (the percentage of time when AGV is not in use); and
- AGV active rate (the percentage of time when AGV is in use, including both empty and full moves).
While changing the dispatching rules, and keeping all other inputs fixed, the simulation model showed the variation in the number of served containers, as well as in the number of containers waiting in the queue for AGVs.

3.4. Description of the proposed DEA Model

When import containers are unloaded from a ship, they form a queue at Berth, waiting to be transferred from Berth to Storage yard, Gate or Train buffer by AGV fleet. In this study, twelve proposed scenarios for import containers dispatching from Berth to storage areas, as DMUs, were evaluated. The objective of an AGV fleet manager is to transfer (serve) containers to assigned locations during the shortest possible time interval, and to minimize waiting time of containers in the queue. Thus, an efficient scenario should employ AGV fleet that maximizes the number of served containers and minimizes the number of containers in a queue during the observed time interval.

Very important step in the DEA model development is the proper selection of inputs and outputs. In the first formulation of DEA model for this study, authors had used number of AGVs, number of container in the queue and AGV idle rate as inputs and the number of served containers as output. However, after correlation analysis and the analysis of how the change in inputs and outputs impacts the efficiency of observed scenarios, the DEA model with two inputs—number of AGVs and AGV active rate—and two outputs—reciprocal value of the number of containers in the queue and the number of served containers—was chosen.

4. Results

4.1. Results of the Simulation Experiments

Table 1 shows the comparison between observed scenarios for the number of served containers and the number of containers in queue. The results indicated that it is necessary to use 23 AGVs in order to keep ship turnaround time within the limits of one business day (two shifts). The dispatching rule the “smallest distance” provided the highest number of served containers and the lowest number of containers in the queue.

Table 2 shows active and idle rates of AGVs depending on their number and the dispatching rule for all 12 observed scenarios. Values of these measures, with respect to the number of AGVs, were not considerably different (less than 2% difference). However, with respect to the dispatching rule, the differences between these measurements were higher (from 3% to 9%). Thus, it was not possible to conclude which scenario is the most suitable for the observed container terminal.

<table>
<thead>
<tr>
<th>Number of AGVs</th>
<th>Cyclic</th>
<th>Random</th>
<th>Smallest distance</th>
<th>Largest distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of served containers</td>
<td>Number of containers in queue</td>
<td>Number of served containers</td>
<td>Number of containers in queue</td>
<td>Number of served containers</td>
</tr>
<tr>
<td>18</td>
<td>1554</td>
<td>148</td>
<td>1575</td>
<td>133</td>
</tr>
<tr>
<td>20</td>
<td>1613</td>
<td>105</td>
<td>1625</td>
<td>103</td>
</tr>
<tr>
<td>23</td>
<td>1712</td>
<td>76</td>
<td>1711</td>
<td>62</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Number of AGVs</th>
<th>Cyclic</th>
<th>Random</th>
<th>Smallest distance</th>
<th>Largest distance</th>
</tr>
</thead>
<tbody>
<tr>
<td>AGV idle rate</td>
<td>AGV active rate</td>
<td>AGV idle rate</td>
<td>AGV active rate</td>
<td>AGV idle rate</td>
</tr>
<tr>
<td>18</td>
<td>0.06</td>
<td>0.94</td>
<td>0.03</td>
<td>0.97</td>
</tr>
<tr>
<td>20</td>
<td>0.06</td>
<td>0.94</td>
<td>0.04</td>
<td>0.96</td>
</tr>
<tr>
<td>23</td>
<td>0.08</td>
<td>0.92</td>
<td>0.05</td>
<td>0.95</td>
</tr>
</tbody>
</table>
Simulation results did not provide substantial differences between observed scenarios, thus, it was not possible to draw a clear conclusion of which scenario is the most suitable for the analyzed terminal. For that reason, DEA was used to analyze the efficiency of proposed alternatives and show their rank based on the data obtained from the simulation experiments.

4.2. Evaluating the Efficiency of Proposed Scenarios at Port Container Terminal

Analysis of the simulation results indicated that the “smallest distance” rule provided the best scenario regarding the number of served containers and the number of containers in the queue, under the assumption about the number of employed AGVs. Analysis of AGVs idle rates and AGVs active rates showed that the values of these rates were very close among scenarios, thus, it was not possible to make a decision of which scenario could be considered the best. For that reason, this study proposed the use of DEA method. DEA method provides the opportunity to evaluate the efficiency, as well as to rank competitive dispatching rules, considering number of employed AGVs, number of containers in the queue (that are waiting for AGVs), AGV utilization, and number of served containers in the observed time interval.

This study evaluated 12 scenarios for containers dispatching from Berth to storage areas; each scenario represents a separate DMU, as follows:
- DMU1: Employment of 18 AGVs with dispatching rule “cyclic”;
- DMU2: Employment of 20 AGVs with dispatching rule “cyclic”;
- DMU3: Employment of 23 AGVs with dispatching rule “cyclic”;
- DMU4: Employment of 18 AGVs with dispatching rule “random”;
- DMU5: Employment of 20 AGVs with dispatching rule “random”;
- DMU6: Employment of 23 AGVs with dispatching rule “random”;
- DMU7: Employment of 18 AGVs with dispatching rule “smallest distance”;
- DMU8: Employment of 20 AGVs with dispatching rule “smallest distance”;
- DMU9: Employment of 23 AGVs with dispatching rule “smallest distance”;
- DMU10: Employment of 18 AGVs with dispatching rule “largest distance”;
- DMU11: Employment of 20 AGVs with dispatching rule “largest distance”;
- DMU12: Employment of 23 AGVs with dispatching rule “largest distance”.

Analysis of proposed scenarios at container terminal using DEA methodology was done with the purpose of ranking them. For this evaluation, the inputs were the number of employed AGVs and AGVs active rate, while the reciprocal value of the number of containers in the queue and number of served containers were the outputs. Software Efficiency Measurement System (n.d.) was used to solve suggested DEA models. Table 3 shows inputs and outputs, as well as calculated efficiencies for the proposed DEA model.

Table 3. The efficiencies of evaluated scenarios

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Number of employed AGVs</th>
<th>AGVs active rate</th>
<th>Reciprocal value of the number of containers in the queue</th>
<th>Number of served containers</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td>DMU1</td>
<td>18</td>
<td>0.94</td>
<td>0.0068</td>
<td>1554</td>
<td>95.40%</td>
</tr>
<tr>
<td>DMU2</td>
<td>20</td>
<td>0.94</td>
<td>0.0095</td>
<td>1613</td>
<td>94.49%</td>
</tr>
<tr>
<td>DMU3</td>
<td>23</td>
<td>0.92</td>
<td>0.0132</td>
<td>1712</td>
<td>95.91%</td>
</tr>
<tr>
<td>DMU4</td>
<td>18</td>
<td>0.97</td>
<td>0.0075</td>
<td>1575</td>
<td>96.69%</td>
</tr>
<tr>
<td>DMU5</td>
<td>20</td>
<td>0.96</td>
<td>0.0097</td>
<td>1625</td>
<td>93.98%</td>
</tr>
<tr>
<td>DMU6</td>
<td>23</td>
<td>0.95</td>
<td>0.0161</td>
<td>1711</td>
<td>94.10%</td>
</tr>
<tr>
<td>DMU7</td>
<td>18</td>
<td>0.93</td>
<td>0.0127</td>
<td>1629</td>
<td>100.00%</td>
</tr>
<tr>
<td>DMU8</td>
<td>20</td>
<td>0.92</td>
<td>0.0204</td>
<td>1685</td>
<td>100.00%</td>
</tr>
<tr>
<td>DMU9</td>
<td>23</td>
<td>0.91</td>
<td>0.0714</td>
<td>1774</td>
<td>100.00%</td>
</tr>
<tr>
<td>DMU10</td>
<td>18</td>
<td>1.00</td>
<td>0.0061</td>
<td>1531</td>
<td>93.98%</td>
</tr>
<tr>
<td>DMU11</td>
<td>20</td>
<td>1.00</td>
<td>0.0078</td>
<td>1607</td>
<td>90.63%</td>
</tr>
<tr>
<td>DMU12</td>
<td>23</td>
<td>1.00</td>
<td>0.0095</td>
<td>1662</td>
<td>88.71%</td>
</tr>
</tbody>
</table>
Based on the calculated values, the following AGV dispatching rules were efficient:

- **DMU7**: Employment of 18 AGVs with dispatching rule “smallest distance”;
- **DMU8**: Employment of 20 AGVs with dispatching rule “smallest distance”;
- **DMU9**: Employment of 23 AGVs with dispatching rule “smallest distance”;

It was necessary to determine which of these efficient DMUs was the most efficient. For the purpose of ranking these efficient DMUs, the method of super-efficiency was used (Anderson & Peterson, 1993). The results are shown in Table 4. This method provides the way to rank the efficient DMUs (DMU7, DMU8, and DMU9), and to choose the unit with the highest efficiency. The most efficient unit was DMU9.

**Table 4. The rank of evaluated scenarios**

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Inputs</th>
<th>Outputs</th>
<th>Efficiency</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Number of employed AGVs</td>
<td>AGVs active rate</td>
<td>Reciprocal value of the number of containers in the queue</td>
<td>Number of served containers</td>
</tr>
<tr>
<td>DMU1</td>
<td>18</td>
<td>0.94</td>
<td>0.0068</td>
<td>1554</td>
</tr>
<tr>
<td>DMU2</td>
<td>20</td>
<td>0.94</td>
<td>0.0095</td>
<td>1613</td>
</tr>
<tr>
<td>DMU3</td>
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<td>0.92</td>
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<td>DMU4</td>
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<td>DMU5</td>
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<td>DMU7</td>
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<td>0.93</td>
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<tr>
<td>DMU8</td>
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<td>0.92</td>
<td>0.0204</td>
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<tr>
<td>DMU9</td>
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<td>1531</td>
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<tr>
<td>DMU11</td>
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<td>1.00</td>
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</tr>
<tr>
<td>DMU12</td>
<td>23</td>
<td>1.00</td>
<td>0.0095</td>
<td>1662</td>
</tr>
</tbody>
</table>

Table 4 shows that the dispatching rule “smallest distance” with employment of 23 AGVs gave the highest efficiency. It was considerably higher than the efficiency of two following dispatching rules “smallest distance” with employment of 18 AGVs and “smallest distance” with employment of 20 AGVs. The lowest ranked rule was “largest distance” with employment of 23 AGVs.

### 5. Conclusion

In this paper, part of the considered automated port container terminal was simulated. The observed process started from the moment of unloading containers from the container ship. Quay cranes unloaded import containers at Berth, and containers were further transported to the storage areas using AGVs.

The objective of this study was to analyze the difference in the number of served import containers based on the number of employed AGVs and their dispatching rules. The dispatching rules for AGVs movement on container terminal were “cyclic”, “random”, “smallest distance”, and “largest distance”. Also, simulation experiments varied the number of employed AGVs: 18, 20 and 23. Collected and analyzed MOEs were the number of served containers, the number of containers in the queue, AGV idle and active rates. Simulations results indicated the differences in the number of served containers and in the number of containers in the queue waiting for the AGVs at the Berth. If 23 AGVs were employed, it was possible to keep ship turnaround time within one business day (within two shifts). Dispatching rule the “smallest distance” provided the highest number of served containers and the lowest number of containers in the queue within simulated time interval. The differences among AGVs idle and active rates regarding number of AGVs were insignificant. The same MOEs analyzed regarding the dispatching rule differed among each other in the range from 3% to 9%. Based on these small differences for AGVs idle and active rates in observed scenarios, it was not possible to make a decision of which scenario was the most suitable for the observed container terminal.

For that reason, this study used DEA methodology to evaluate the efficiency of proposed alternatives and to show their rank taking the measurements from the simulation results. The super-efficiency DEA model ranked competitive dispatching rules, including in the calculations number of employed AGVs, AGVs active rate, reciprocal value of the number of containers in the queue, and number of served containers. As expected, the “smallest distance” dispatching rule with the highest number of employed AGVs (23) proved to be the most
efficient. Next was the “smallest distance” dispatching rule with 18 employed AGVs; followed by the “smallest distance” rule with 20 employed AGVs. While the “largest distance” dispatching rule with 23 employed AGVs had the lowest rank.

Using basic DEA method, all three scenarios that used “smallest distance” dispatching rule had shown to be efficient. However, the super-efficiency DEA method showed that the employment of 23 AGVs provided the significantly higher efficiency (354%) compared to the employment of 18 or 20 AGVs. Although the efficiency of the employment of 18 AGVs was higher than the efficiency of the fleet of 20 AGVs, which was not expected, their efficiencies were very close in value (104% and 100%). These values indicate that having a fleet of 18 or 20 AGVs will not change the performance of the system considerably, but expending the fleet to 23 AGVs will significantly increase the system efficiency. Also, the results indicate that “cyclic”, “largest distance” and “random” dispatching rules are not appropriate choices for this type of container terminal, regardless of the number of employed AGVs.

This study pointed to the importance of the appropriate choice of both number of employed AGVs and the AGVs dispatching rule, since the terminal productivity changed with the variation in either of these two values. Furthermore, this study pointed to the fact that simulation, often the first and only choice for the planners, is not sufficient tool in deciding on the number of employed AGVs and their dispatching rules.

The results of this study, based on the simulation experiments and used DEA model, are important for planning the process of handling import containers at port container terminal. However, the cost analysis would provide more information on the observed process; thus, it could be the subject of the future work.

References

