Investigating Efficiency Utilizing Data Envelopment Analysis: A Case Study of Shipyards

Glenda Mayo, Omidreza Shoghli and Tyler Morgan

November 8, 2019

INVESTIGATING EFFICIENCY UTILIZING DATA ENVELOPMENT ANALYSIS A CASE STUDY OF SHIPYARDS

Glenda Mayo Ph.D.[1], Omidreza Shoghli Ph.D.[2], Tyler Morgan[3]
[1]Department of Engineering Technology and Construction Management, UNC Charlotte, 9201 University City Blvd, Charlotte, NC 28223-0001; PH (704) 687-5047; email: gmayo4@uncc.edu
[2]Department of Engineering Technology and Construction Management, UNC Charlotte, 9201 University City Blvd, Charlotte, NC 28223-0001; PH (704) 687-5047; email: oshoghli@uncc.edu
[3]Department of Engineering Technology and Construction Management, UNC Charlotte, 9201 University City Blvd, Charlotte, NC 28223-0001; PH (704) 687-5047; email: tmorga41@uncc.edu

ABSTRACT
Establishing performance targets for marine maintenance and repair operations can be challenging for management due to the multitude of factors that can potentially influence productivity, efficiency, and manpower requirements. The aim of this study was to measure and evaluate the efficiencies of various maintenance and repair shipyard operations using Data Envelopment Analysis (DEA) methodology. Results presented in this study were used to develop an overall strategic plan for enhanced decision-making with regards to labor and resource requirements and management strategies for the administration of the shipyards. Inefficient maintenance operations were identified through DEA evaluation and included the use of identified quantitative and qualitative factors. The results of the study indicate that the qualitative research assisted to confirm the results of the quantitative portion of the study. Additionally, the researchers were able to make specific recommendations to the shipyard operations concerning potential improvements.

INTRODUCTION
Ferry operators participating in the 2014 National Census of Ferry Operators (NCFO) survey state that U.S. ferries carried over 115 million passengers and just over 30 million vehicles in the year 2013 (Steve et al., 2016). The importance of maintaining assets for ferry operations directly influences the services provided to millions of passengers each year. A shipyard along the east coast stated that over the years, the number of personnel at their particular operation has decreased although the number of vessels has increased (Stegall, 2018). Additionally, Coast Guard polices require that all ferries to be dry-docked twice every five (5) years for maintenance, repair, and inspection which limits flexibility in scheduling. The increased maintenance levels for ferry vessels affect the planned workforce levels, staffing needs, resource requirements. Therefore, the number of personnel for an operation is an important factor in not only ensuring the needs for vessel repair and maintenance, but also to the success of the entire maintenance operation's mission. Staff shortages can affect personnel workloads, stress, and productivity. Long-term effects may also include low morale and absenteeism and can become a systemic issue that is difficult to redirect (LaMartin and Powell, 1980; Shirouyehzad et al.). This is especially important in the maintenance and repair industry where most operations are heavily dependent on skilled trades and manual labor.

BACKGROUND
To accurately evaluate the efficiency of an operation, all factors potentially affecting productivity and the production process must be considered. Therefore, manpower studies can be difficult because of the vast number of variables affecting productivity. Determining efficiency is also more challenging for public agencies, who have typically struggled with the concept. As opposed to a manufacturing setting, public organizations and other service-related industries do not produce a product; instead, they provide imperative services to their customers making quantification of productivity and efficiency even more challenging.

Traditional approaches to measuring shipyard productivity have included generic calculations with a weakness because they provide little insight into the causes of productivity changes, especially when considering that some apply best to ship building vs. ship maintenance (LaMartin and Powell, 1980; Pires and Lamb, 2008). The approach presented in this research uses Data Envelopment Analysis (DEA) as a method of evaluating efficiency in shipyard operations. DEA is a methodology that may be used as a human resource indicator and corrects some of the previously mentioned weaknesses (Monika & Mariana, 2015). The main advantage of DEA, with respect to other methodologies, is that DEA has the capability to handle multiple inputs and outputs (Charnes et al., 1978). DEA is a methodology designed to assess how efficiently a firm, organization, agency, program, or site produces the outputs (or services) it has been charged to produce. This advantage in DEA is the benefit as an analysis for determining efficiency because the effort requires a level of pragmatic investigation into the realistic operations. Moreover, DEA can be used as a forecasting and benchmarking tool as well as a tool for establishing performance targets in multiple industries. This research uses the efficient frontier and efficiency scores provided by DEA, along with qualitative measures identified through conversation with industry experts to recommend methods of determining optimal organizational hierarchy, manpower levels, and shipyard scheduling for efficient and effective operations.

LITERATURE

The significance found in the literature stems from the need to assess the ability to evaluate marine maintenance and repair operations and determine corrective action in cases of inefficiency. Table 1 lists what the authors felt were relevant materials and the application areas/uses of DEA.

Table 1: Historical Applications of DEA

Author	Application Area	Description
Carnes et al. (1998)	Energy	Study to evaluate and benchmark energy consumption of buildings in terms of productivity
McCabe et al. (2005)	Construction	Use of DEA to establish benchmarks for contractor prequalification
Ozbek (2007)	Transportation	Study of the efficiency of bridge maintenance
Trappey and Chiang (2008)	New Product Development	DEA as a benchmarking technique for planning
Abdullah et al. (2012)	Company	DEA to determine efficiency of internal company projects
Shirouyehzad et al. (2012)	Employee	DEA to measure employee efficiency
Monika and Mariana (2015)	Human Resources	DEA as human resource controlling tool
Zhang et al. (2015)	Transportation	Study of the efficiency of bridge replacement and rehabilitation programs
Visani et al. (2016)	Ownership	DEA as a means of determining total cost of ownership
Marchetti and Wanke (2016)	Transportation	Study of the efficiency of Brazil’s freight transportation by rail

RESEARCH OBJECTIVES & METHOD

Research Objectives

The purpose of this research is to develop a methodology that combines qualitative and quantitative data to assist in determining efficiency levels for shipyard operations. Although DEA has been used for years to determine efficiency, the purpose of the qualitative evaluation in this study is to assess operations based on realistic factors identified by industry experts. Once the qualitative and quantitative assessments were conducted, the results of the analysis for each were compared to determine whether the efficiencies represented by DEA match the results of the qualitative analysis.

Maintenance and Repair Facilities Overview

To evaluate the efficiency, one shipyard was considered the "customer" of the study and is labeled Shipyard A. The research team conducted visits and held interviews with industry experts from other ship repair facilities that are similar in operation and those operations were compared to Shipyard A. Due to the limited number of shipyards and competitiveness of the industry, the majority of the 10 shipyards contacted were unwilling to participate or provide operational data. Three shipyards agreed to participate in this study fully while an additional shipyard agreed to a visit but disinclined to offer any operational data. Due to the nature of this research and confidentiality agreements, the names of shipyards will remain anonymous. However, it is important to note that the responses included both public and private shipyards. Shipyard operations, especially when considering the differences between public and private entities, can vary greatly. A multifactor perspective was considered in the research and the four basic steps are listed below. The results also outline, in this order, the descriptions and discussion of each research step.

- Step 1 – Data collection through shipyard visits, interviews, and surveys
- Step 2 – Determine qualitative factors and complete qualitative assessment of operations
- Step 3 – Quantitative assessment of shipyard operations using DEA
- Step 4 – Analyze assessment results and compare quantitative and qualitative assessments

To provide a realistic comparison, the shipyards were identified by their size. The most appropriate description of the shipyards similar in operation to Shipyard A, includes those in a category titled, Repair Yards with Drydock Facilities (Major Shipyards) and an additional category titled, Medium and Small Shipyards. Repair Yards with Drydock Facilities are defined as those facilities having at least one drydocking facility that can accommodate vessels 400 feet in length and over, provided that water depth in the channel leading to the shipyard is at least 12 feet (MARAD, 2004). These facilities are also capable of constructing a vessel less than 400 feet in length overall. To classify the participating shipyards (Table 2), this research utilized the shipyard classifications and definitions provided in a report by the U.S. Department of Transportation Maritime Administration (MARAD) on U.S. Shipbuilding and Repair Facilities. These classifications are based on the joint U.S. Navy and MARAD 1982 Shipyard Mobilization Base Analysis, or SYMBA (MARAD, 2004). The participating shipyards included four facilities as shown in Table 2 (Shipyard E would only participate in the Qualitative portion of the study), and also summarizes the basic demographics of the shipyards by size, type, # of employees and the basic organizational structure (indicating the primary responsibility for the maintenance project schedules).

Table 2: Shipyard General Characteristics

Shipyard	Shipyard Classification	Org. Type	M&R Labor	FTEs	Org. Structure	Max. Drydock Capability	Apprentice Program
Shipyard A (SY_A)	Medium/ Small	Public	In-house only	65	5 Levels – Shipyard Superintendent	867 tons, 220' LOA x 50' Wide	No
Shipyard B (SY_B)	Major	Private	In-house and subcontracted	250	4 Levels – Project Manager	8,100 tons, 341' LOA x 110' Wide	No
Shipyard C (SY_C)	Medium/ Small	Private	In-house and subcontracted	25	4 Levels – VP/ Superintendent/ Estimator	480 tons, 200' LOA x 38' Wide	No
Shipyard D (SY_D)	Major	Private	In-house and subcontracted	380	5 Levels – Project Manager	89,600 tons, 751' LOA x 110' Wide	Yes
Shipyard E (SY_E)	Major	Private	In-house and subcontracted	Un-disclosed	4 Levels – Supervisor	17,640 tons, 620' LOA x 88' Wide	Yes

Methodology

While there are various software programs available to carry out the DEA process, the software program utilized was Performance Improvement Management Software (PIM-DEA). PIM-DEA allows for multiple variations of DEA models to be developed and carried out simultaneously, which provided several advantages with respect to identifying sources of inefficiencies amongst DMUs.

The production influencers, or DEA model inputs and outputs are inclusive indices relating to shipyard capacity, shipyard employment levels, shipyard technology levels and operational strategies, labor productivity, and refurbishment time. These production parameters (Table 3) were selected based on their relevancy to the ship repair industry, the availability and accessibility of data, and the measurability, and quantification.

Table 3: Analysis Inputs and Outputs

	Variable Description	Abbreviation	Unit of Measure
Inputs	Shipyard Capacity	SYC	-
	Number of Employees	#EMP	-
	Qualitative Factor	QUAL	-
Outputs	Labor Productivity	PROD	cgt/hr
	Refurbishment Time	RTIME	1/days

RESULTS AND FINDINGS

The results, as well as a comparison of the results, of both the qualitative assessment and the quantitative assessments are provided. The comparison of the qualitative and quantitative information also contributed important findings for the research. However, it should be noted that due to the limited number of participants, many of the participating shipyards most likely felt that they are efficient which lead to their willingness to share data. Therefore, the comparison is with some of the most efficiently operating shipyards on the U.S. east coast. The results should be interpreted to be an excellent benchmark for the shipyard operations as opposed to benchmarking with “average” operations.

Qualitative Results

The qualitative assessment of the participating shipyards was carried out using a three-step process with the first step being inclusive of visits to shipyards and conducting interviews with shipyard representatives. Using these observations and the prominence of the topics in the conversations, two separate components were identified for use in the qualitative assessment: Technology and Management/Manpower Strategies. As shown in Table 4, each component is comprised of subcategories. These subcategories represent important qualitative factors related to shipyard performance as identified by industry experts.

The second step of the qualitative assessment required applying the qualitative factors to a matrix format for each shipyard to be scored according to their levels of implementation. The final step of the qualitative assessment involved summing the scores attained in the matrix and ranking the shipyards based on their qualitative factors. The completed matrix along with the associated shipyard rankings can be seen in Table 4.

Table 4: Qualitative Assessment Results

Qualitative Assessment Component	MH	SY B	SY C	SY D	SY E
Technology					
Advanced Machinery	1.00	3.00	1.00	4.00	1.00
CMMS	3.00	2.00	1.00	1.00	1.00
Management/Manpower Strategies					
Organizational Structure	1.00	4.00	1.00	5.00	1.00
Planning and Scheduling	2.00	5.00	1.00	3.00	1.00
Efficiency Strategies	1.00	4.00	1.00	3.00	1.00
Apprenticeship Program	1.00	1.00	1.00	5.00	4.00
Outsourced Labor	1.00	3.00	3.00	5.00	4.00
Total Score out of 40	**10.00**	**22.00**	**9.00**	**26.00**	**13.00**
Qualitative Assessment Ranking	**2**	**4**	**1**	**5**	**3**

The qualitative assessment ranking given to the shipyards was based on a scale of one to five with one being the lowest ranking and five being the highest ranking. As shown in Table 4 Shipyard D received the highest ranking, while Shipyard C received the lowest overall ranking of all shipyards. The results of the qualitative assessment suggest that based on the qualitative factors evaluated, Shipyard B and Shipyard D should achieve higher performance than the other three shipyards. In other words, based solely on the qualitative factors related to shipyard performance, Shipyard B and Shipyard D should represent the “best practice” units or efficient DMUs in the DEA assessment of quantitative operational data.

The Qualitative Factor or QUAL input variable was developed using the data provided in the qualitative assessment along with a pairwise comparison of the various qualitative components. To perform the pairwise comparison, a survey was sent out to industry professionals that asked to evaluate the level of importance of each qualitative category with respect to shipyard productivity. An index of one through seven (1 – 7) was utilized with one (1) being least important and seven (7) being most important. In total, eight industry professionals from various eastern shipyards responded to the survey. The participants were inclusive of both internal employees at the compared Shipyard A, as well as experts from the participating shipyards. Due to space limitations, the specifics of the pairwise comparison are briefly described to enable the focus to be on the quantitative assessment and DEA. However, Table 5 shows the resulting weighting factor for each category was determined by the product of points received in the pairwise comparison.

Table 5: Qualitative Factor Input Variable Results

	Pairwise Score	Weight	MH	SY B	SY C	SY D
Advanced Machinery	4	0.19	0.19	0.571	0.19	0.761
CMMS	1.5	0.071	0.214	0.143	0.071	0.071
Organizational Structure	6	0.285	0.285	1.142	0.285	1.427
Planning and Scheduling	5	0.238	0.476	1.189	0.238	0.714
Efficiency Strategies	3	0.143	0.143	0.571	0.143	0.428
Apprenticeship Program	1.5	0.071	0.071	0.071	0.071	0.357
Outsourced Labor	0	0.001	0.001	0.003	0.003	0.005
		Total	**1.381**	**3.69**	**1.002**	**3.763**
QUAL Variable (Total x 1000) =			**1380.57**	**3689.79**	**1002**	**3763.14**

Quantitative Results

To develop the Qualitative Factor (QUAL) input variables for use in the analysis, the data from the initial qualitative assessment (Table 5) were used in conjunction with the quantitative variables to assess the ship yards. The first step for the analysis was to establish and refine the available data to determine values for the input and output variables for DEA. The decision-making units (DMUs) used in the analysis included the individual work orders for dry-dock repairs from each shipyard. In total 15 DMUs or work orders were included in the analysis, and used three input variables (Shipyard Capacity, Number of Employees, and Qualitative Factor) and two output variables (Labor Productivity and Refurbishment Time). The 15 DMUs and five input/output variables provide adequate discriminatory power for the DEA model as stated in the literature. Prior to performing the DEA Assessment, three input variables utilized by this research, Shipyard Capacity (SYC), Number of Employees (#EMP), and Qualitative Factor (QUAL), are related to the characteristics of the shipyard from an overall prospective; hence the input variables were only calculated four times, once for each shipyard and then applied to the appropriate work orders. On the other hand, the two outputs, Labor Productivity (PROD) and Refurbishment Time (RTIME) require calculation for each individual work order. The Shipyard Capacity (SYC) variable is expressed as a composite index related to the maximum drydocking capacity of each shipyard in gross tons, length and width of vessel. The SYC variable was calculated by normalizing the data for each representative capacity and averaging the three normalized capacities for each shipyard. The average of the normalized capacities was then multiplied by 1000 to develop the final SYC variable. The maximum vessel capacities along with the calculated SYC variable for each shipyard are presented in Table 6.

Table 6: Maximum Shipyard Capacities

Shipyard	**Maximum Vessel Capacity**			**Shipyard Capacity (SYC)**
	Gross Tons	**Length (ft.)**	**Width (ft.)**	
Shipyard A (SY_A)	867	220	50	1149

Shipyard B (SY_B)	8100	341	110	1971
Shipyard C (SY_C)	480	200	38	1000
Shipyard D (SY_D)	89600	751	110	3245

The second input variable used in the analysis is Number of Employees (#EMP). The #EMP variable for each shipyard is established based on the number of full-time in-house employees working for each shipyard. The Number of Employees variable does not include subcontracted labor utilized by the shipyards because it is difficult to determine with accuracy and varies from project to project. Employment data is based on the information provided to the research team during the visits conducted with each shipyard as well as the operational data received from the shipyards. The Number of Employees (#EMP) for each shipyard is as follows: Shipyard A–65, Shipyard B–250, Shipyard C–25, and Shipyard D–380.

The final input variable utilized in the analysis is the Qualitative Factor (QUAL) for each shipyard previously determined. The productivity and efficiency in shipyards are affected by factors indirectly related to the production processes. The purpose of the Qualitative Factor is to account for these indirect production influencers within the DEA model. In combination with the input variables, the DEA models in the analysis utilize two output variables to represent shipyard performance. The first of these variables is expressed as Labor Productivity (PROD) in units of hours per compensated gross ton (CGT). Labor Productivity must consider the size and type of vessel under repair. Thus, the common unit of measurement compensated gross ton (CGT) was utilized to account for these characteristics in the Labor Productivity calculation as described in the literature, however the calculation includes the gross tonnage of the vessel along with factors representing the type of vessel and the influence of ship size to develop the unit CGT. The Labor Productivity (PROD) variable expresses a productivity rate for each work order (DMU) based on the total hours required to complete the repairs and the CGT of the vessel under repair. To compute the PROD variable, the total hours for each work order along with the CGT of the vessel under repair were calculated. PROD was then determined by dividing the total hours by the CGT of the vessel. Nonetheless, because this research utilizes PROD as an output variable, the final PROD variable used in the DEA model must be represented by the inverse of CGT per hour. This is because an increase in the PROD variable must represent an improvement to performance due to the requirements of DEA or in other words, a reduction in hours per CGT. Therefore, the final variable used in the DEA model is expressed in units of CGT per hour, where an increase in the productivity rate represents a reduction in hours per CGT. The calculated Labor Productivity (PROD) for each work order is shown in Table 7.

Table 7: Labor Productivity (PROD) Rates

DMUs	Total Hours	CGT	Productivity (hr/cgt)	PROD (cgt/hr)
DMU - A1	13617.75	1002.51	13.584	0.074
DMU - A2	11937.50	2243.05	5.322	0.188
DMU - A3	6427.40	2068.80	3.107	0.322
DMU - A4	7040.70	1425.09	4.941	0.202
DMU - A5	13004.40	1347.14	9.653	0.104
DMU - A6	13450.60	1424.48	9.442	0.106
DMU - A7	4211.00	1982.66	2.124	0.471
DMU - A8	11128.75	1336.95	8.324	0.120

DMU - A9	18007.10	1078.84	16.691	0.060
DMU - B1	3651.50	2595.82	1.407	0.711
DMU - B2	3955.50	943.03	4.194	0.238
DMU - B3	1590.50	1021.60	1.557	0.642
DMU - B4	4410.00	1025.28	4.301	0.232
DMU - C1	5124.25	293.47	17.461	0.057
DMU - D1	23347.00	47264.33	0.494	2.024

The final variable used in the analysis, Refurbishment Time (RTIME) is utilized to represent the total number of days a vessel was dry-docked for repairs. The time required to complete vessel repairs is a critical factor in determining the competitive potential of a shipyard and is directly related to shipyard performance. Therefore, RTIME was chosen as an output variable for the DEA model because it is a key indicator of operational performance. In this research, RTIME is expressed as the inverse of total days (1/days) multiplied by 1000. Similar to the Labor Productivity, RTIME is expressed as the inverse of total days because it is utilized as an output variable. Meaning an increase in RTIME must correlate with improved operational performance. In other words, an increase in RTIME must represent a reduction in the total days required for repairs. Consequently, the inverse of total days is used as the unit of measure for RTIME. The total days for each work order (DMU) along with the representative RTIME values are shown in Table 8.

Table 8: Refurbishment Time (RTIME) per DMU

DMUs	Total Days	RTIME
DMU - A1	156.00	6.410
DMU - A2	106.00	9.434
DMU - A3	120.00	8.333
DMU - A4	106.00	9.434
DMU - A5	195.00	5.128
DMU - A6	168.00	5.952
DMU - A7	78.00	12.821
DMU - A8	107.00	9.346
DMU - A9	169.00	5.917
DMU - B1	22.00	45.455
DMU - B2	48.00	20.833
DMU - B3	35.00	28.571
DMU - B4	47.00	21.277
DMU - C1	260.00	3.846
DMU - D1	16.00	62.500

DEA was carried out using both the CCR and BCC envelopment models in the output-orientation. The main variance between the two models is the returns-to-scale (RTS) used in each. The CCR model uses a constant-return-to-scale (CRS) and the BCC model uses a variable-return-to-scale (VRS) and the frontier surfaces formed by the models are different. The surface developed by the CCR model is characterized by a straight line starting at the origin and passing through the first DMU encountered as it approaches the efficient frontier. The use of both the CCR and BCC models allows scale efficiency to be considered which enables inefficiencies within the model to be attributed to either inefficient operations, disadvantageous shipyard conditions, or both.

The relative efficiency evaluation of the participating shipyards repair operations was carried out using the empirical data relating to shipyard performance indicators for 15 separate work orders. Nine work orders (vessels) were from Shipyard A, four work orders were from Shipyard B, and Shipyard C and Shipyard D each provided one work order. The results presented by iterations of the DEA model are relative to the abovementioned data set. The relative efficiency scores generated by both the CCR and BCC models as well as the accompanying scale efficiencies are presented in Table 10. The results present DMUs A7, B1, and D1 as relatively efficient in both the CCR and BCC models, while DMU C1 is relatively efficient only in the BCC model. It is interesting to note that all four of the participating shipyards had a work order receive a relative efficiency score of 100 in the BCC model. Outside of the efficient DMUs, the remaining DMUs under evaluation were considered relatively inefficient by both the CCR and BCC models. When looking at the scale efficiencies of each DMU, only DMU B3 and DMU C1 received scale efficiencies less than 100. As stated previously, SE = CCR/BCC or SE = TE/PTE and a scale efficiency of less than 100 represents disadvantageous conditions within the shipyard. Moreover, a BCC or pure technical efficiency (PTE) score of less than 100 represents inefficient operations within the shipyard. Therefore, it can be said that DMU C1's inefficiency is caused by disadvantageous shipyard conditions and that in terms of shipyard operations DMU C1 is operating efficiently. On the other hand, it can be understood that DMU B3's inefficiency is caused by both inefficient operations as well as disadvantageous shipyard conditions. For the remaining inefficient DMUs, the sources of inefficiencies represented by the results of the DEA models can be attributed purely to inefficient operations. Although the above results represent the relative efficiencies of all four shipyards, the efficiency scores of Shipyard A will primarily be discussed in detail, as the goal of this research is to provide analytical results to improve operations and to aid in developing an overall strategic decision-making plan for the shipyard.

Results presented in Table 9 show that of all completed work orders from Shipyard A only DMU A7 is considered relatively efficient and all other work orders received efficiency scores of less than 75 by both the CCR and BCC models. While DMU A7 is considered relatively efficient by both models, further investigation into the data provided by the shipyard reveals that the efficiency score for DMU A7 shown in the DEA models may be misleading. It was explained that there are times in which vessels are returned to service before it can be fully refurbished. These instances are for various reasons, but most of the time it is the direct result of schedule overruns within the shipyard. The total hours and the total refurbishment time for work order A7 was significantly less than the other work orders provided by the same shipyard. From examination of the data, it can be inferred that work order A7 was an instance when the ferry was sent back into service prior to a full refurbishment. To better analyze the operational efficiencies of the shipyards, DMU A7 was removed from the data set and the DEA models were carried out again. Results of the DEA Assessment with the exclusion of DMU A7 are presented in Table 9.

Table 9: Analysis Results Excluding DMU A7

DMU	CCR Score	BCC Score	Scale Efficiency
A1	54.24	59.78	90.74
A2	81.98	87.97	93.19
A3	93.01	100.00	93.01
A4	82.73	87.97	94.03
A5	44.66	47.82	93.39

A6	51.05	55.50	91.98
A8	79.08	87.15	90.74
A9	50.07	55.18	90.74
B1	100.00	100.00	100.00
B2	45.83	45.83	100.00
B3	65.56	65.73	99.74
B4	46.81	46.81	100.00
C1	84.61	100.00	84.61
D1	100.00	100.00	100.00

In review of the results of Shipyard A, all of the shipyards units received relatively inefficient scores in the CCR model and only DMU A3 received a relatively efficient score in the BCC model. Overall, four of the eight Shipyard A work orders received efficiency scores of less than 60, while three of the remaining four work orders received efficiency scores of less than 90. These low efficiency scores indicate that Shipyard A is operating at less than 60 percent efficiency on half of their work orders and less than 90 percent efficiency on nearly 40 percent of their work orders in comparison to the best practice units. The results indicate that the conditions of the shipyard are disadvantageous as compared to the best practice shipyards, which contributes to the inefficiency. In other words, the existing conditions at Shipyard A (i.e. number of employees, shipyard capacity, and the qualitative factors) are a contributing factor to the inefficiency.

Of all Shipyard A's work orders, only DMU A3 was considered efficient in either model. DMU A3 received an efficiency score of 100 in the BCC model but an efficiency score of 93.01 in the CCR model. This suggests that DMU A3 is locally efficient but not globally efficient. More specifically, this means that when shipyard conditions are taken into account DMU A3 is relatively efficient but is only 93.01 percent efficient from a pure operations standpoint as compared to the efficient shipyards. For the remaining Shipyard A work orders, the sources of inefficiency are caused by both inefficient operations as well as existing shipyard conditions. This is shown by BCC and scale efficiency scores of less than 100. From an overall prospective, the average efficiency of all Shipyard A's work orders are 67.10 and 72.67 in the CCR and BCC models respectively. This indicates on average Shipyard A's operations are 67.10% efficient in terms of pure operations and 72.67% efficient with the inclusion of shipyard conditions as compared to the best practice units of DMUs B1 and D1.

Overall, the results of the DEA Assessment suggest that on average the maintenance operations at Shipyard A are inefficient compared to the best practice units. As stated previously, Shipyard A's inefficiencies are caused by both disadvantageous conditions within the shipyard as well as pure inefficient operations. Disadvantageous shipyard conditions are represented by the DEA input variables or existing operational conditions of the shipyard. Because the DEA model was output-oriented and aimed at evaluating current shipyard conditions, optimal targets for these conditions are unable to be determined by the results. However, of the inputs used in the DEA models, the sensitivity analysis shows that Number of Employees has the most significant effect on overall efficiency scores, especially the efficiency scores of the CCR model, which represents overall maintenance operation efficiency.

The efficient frontiers developed by the DEA models considering the Number of Employees input variable specifically compared to both outputs, Labor Productivity and Refurbishment Time, are shown in Figures 1 and Figure 2. Work orders from Shipyard A are shown enclosed by a rectangle in both figures. At current employment levels Shipyard A is under performing for both Labor Productivity and Refurbishment Time. In other words, Figures 1 and 2 eal that Shipyard A is inefficient because the shipyard should increase productivity and/or lower refurbishment times at current employment levels.

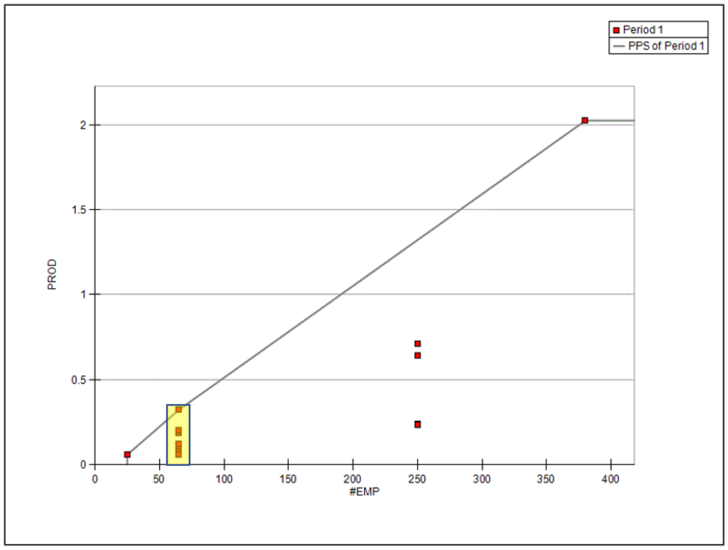

Figure 1: Efficient Frontier - #EMP vs. PROD

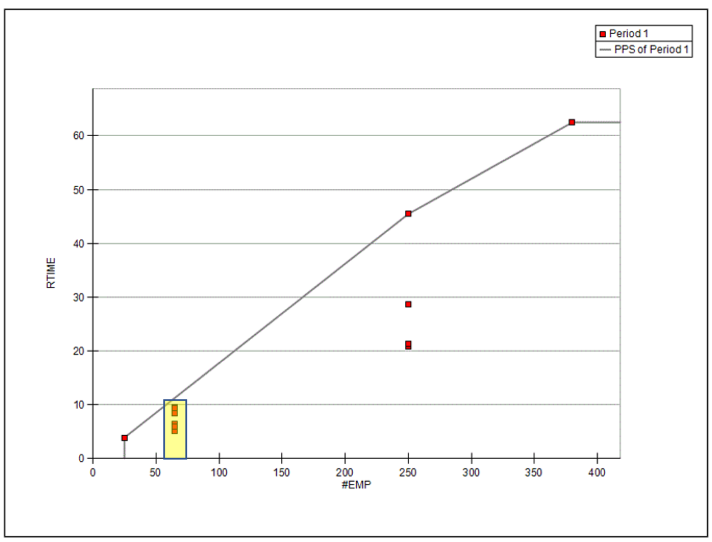

Figure 2: Efficient Frontier - #EMP vs. RTIME

In terms of pure maintenance operations, results of the DEA model allow optimal performance targets for efficient operations to be determined. From the results of the BCC model, with current shipyard conditions, to achieve relative efficiency in comparison to best practice units Shipyard A must improve both Labor Productivity as well as Refurbishment Time on their projects. The results shown indicate that Shipyard A must achieve a DEA Labor Productivity rate on their projects of 0.24 or an actual productivity rate of approximately 4.17 hours per compensated gross ton. Converting from compensated gross tons back to gross tonnage for each ferry class, Shipyard A must achieve a productivity rate of 16.67 hours per gross ton for small Class Ferries, 12.50 hours per gross ton for large Class Ferries, and 14.58 hours per gross ton for medium Class Ferries. In addition to improvements to current productivity rates, with current shipyard conditions, Shipyard A would also have to improve Refurbishment Time on its repair projects. In other words, for the current operations at Shipyard A to become relatively efficient compared to those best practice units, the overall time it takes to complete dry-dock repairs must be reduced. To achieve relative efficient operation, based on the average time of refurbishment Shipyard A would have to reduce the refurbishment time by approximately 33%. In conclusion, the results of the Analysis suggest that Shipyard A would require significant improvements to productivity and refurbishment time performance to become efficient with the work done at best practice shipyards. Based on the qualitative information collected, there are improvements to methods of maintenance used that can assist with the reduction of refurbishment time.

Comparison of Qualitative and Quantitative Results

The results presented by the QUAL input variable calculation match the results shown in the qualitative assessment. Shipyard D received the highest overall score for the QUAL variable followed by Shipyard B, Shipyard A, and Shipyard C, respectively. Similarly, the same results were obtained in the qualitative assessment; however, the inclusion of the weighting factors, or each category's perceived importance to shipyard productivity and efficiency did influence the final results achieved in the QUAL variable calculation. The effect of the weighting factors can be seen when looking at the magnitude of differences among the QUAL variable scores received by each shipyard compared to the results of the qualitative assessment. The results of both the qualitative assessment and QUAL variable calculation suggest that Shipyard B and Shipyard D have advantageous conditions, with respect to qualitative factors related to production, as compared to Shipyards A and C. The results provided by the DEA Assessment of shipyard operations further validate the conclusions drawn from the quantitative assessment. The conclusions drawn from the DEA results coincide with the results found in the qualitative assessment. The two highest scoring shipyards in the Qualitative Assessment both exemplified best practice units in the DEA assessment, while also receiving relatively high scale efficiency scores. Likewise, the two lowest scoring shipyards from the Qualitative Assessment were determined to be inefficient by the results of DEA and received scale efficiency scores less than 100. Additionally, the average scale efficiency scores of the DEA assessment for each shipyard match the shipyard ranks shown in the results of the qualitative assessment. Shipyard D received the highest rank in the Qualitative assessment and received the highest scale efficiency scores in the Analysis. Likewise, Shipyard C received the second highest qualitative rank and scale efficiency scores followed by Shipyard A and Shipyard C in both measures respectively.

Conclusions

The use of DEA has been proven successful in terms of providing efficiency measures for many different industries. However, the implementation of a comparative qualitative analysis assisted in this research to help validate the results. The maintenance and repair process should be investigated thoroughly so that variables selected for efficiency evaluation consider the correct factors affecting productivity for that specific owner. The use of the qualitative data assisted to support the selected variables as well as to compare the quantitative results for validation since the conclusions drawn from the DEA results coincide with the results found in the qualitative assessment. Since the results of the DEA showed inefficiencies in Shipyard A, it was also beneficial to note that DEA utilized agencies that were larger and had more resources and thus provided benchmark opportunities as opposed to highlighting inefficiencies. Since the qualitative and DEA results ranked resources as a need, the researchers were able to recommend some of the qualitative results for recommendations to improve based on potential resources.

References

Abdullah, F., Ku-Mahamud, K. R., Ahmad, F., Ghani, N., & Kasim, M. (2012). Relative Efficiency Assessment of Projects Using Data Envelopment Analysis: A Case Study. *JDCTA: International Journal of Digital Content Technology and its Applications, 6*(9), 310-318.

Carnes, D., Hunn, B., & Jones, J. (1998). *The use of data envelopment analysis for evaluating building energy consumption in terms of productivity*.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*(6), 429-444.

Cook, W. D., & Zhu, J. (2013). *Data envelopment analysis: Balanced benchmarking*: CreateSpace Independent Publishing Platform.

Jalili, M. (2015). *Multi-measure performance assessment of the divisions of the Wyoming Highway Patrol.* Colorado State University.

Lamartin, F., & Powell, E. (1980). Manpower-Profiling Approach to Shipyard Productivity *Naval Engineers Journal, 92*(4), 49-56.

Marchetti, D., & Wanke, P. (2016). Brazil's rail freight transport: Efficiency analysis using two-stage DEA and cluster-driven public policies. *Socio-Economic Planning Sciences*.

McCabe, B., Tran, V., & Ramani, J. (2005). Construction prequalification using data envelopment analysis. *Canadian Journal of Civil Engineering, 32*(1), 183-193.

Monika, D., & Mariana, S. (2015). The Using of Data Envelopment Analysis in Human Resource Controlling. *Procedia Economics and Finance, 26*, 468-475.

Ozbek, M. E. (2007). *Development of a comprehensive framework for the efficiency measurement of road maintenance strategies using data envelopment analysis.*

Ozbek, M. E., de la Garza, J. M., & Triantis, K. (2009). Data envelopment analysis as a decision-making tool for transportation professionals. *Journal of Transportation Engineering, 135*(11), 822-831.

Ozbek, M. E., de la Garza, J. M., & Triantis, K. (2010). Data and modeling issues faced during the efficiency measurement of road maintenance using data envelopment analysis. *Journal of Infrastructure Systems, 16*(1), 21-30.

Pires, F. C. M., & Lamb, T. (2008). Establishing performance targets for shipbuilding policies. *Maritime Policy & Management, 35*(5), 491-502. doi:10.1080/03088830802352129

Rabar, D. (2015). Setting key performance targets for Croatian shipyards. *Croatian Operational Research Review, 6*(1), 279-291.

Shirouyehzad, H., Hosseinzadeh Lotfi, F., Aryanezhad, M., & Dabestani, R. (2012). A data envelopment analysis approach for measuring the efficiency of employees: a case study. *South African Journal of Industrial Engineering, 23*(1), 191-201.

Silkman, R. (1986). Measuring Efficiency: An Assessment of Date Envelopment Analysis. Jossey-Bass Publishers.

Stegall, K. (2018). Quality Assurance Supervisor, Interview Communication, conducted January 2018.

Steve, K., Parker, J., and Reschovsky, C. (2016). "2014: Highlights of Ferry Operators in the United States." https://www.bts.gov/sites/bts.dot.gov/files/docs/browse-statistical-products-and-data/bts-publications/archive/203166/special-report-ncfo-2016.pdf

Trappey, A. J., & Chiang, T.-A. (2008). A DEA benchmarking methodology for project planning and management of new product development under decentralized profit-center business model. *Advanced Engineering Informatics, 22*(4), 438-444.

U.S. Department of Transportation Maritime Administration (MARAD). (2004). Report on Survey of U.S. Shipbuilding and Repair Facilities. Prepared by the office of Shipbuilding and Marine Technology. December 2004.

Visani, F., Barbieri, P., Di Lascio, F. M. L., Raffoni, A., & Vigo, D. (2016). Supplier's total cost of ownership evaluation: a data envelopment analysis approach. *Omega, 61*, 141-154.

Zhang, Z., Agbelie, B. R., & Labi, S. (2015). Efficiency Measurement of Bridge Management with Data Envelopment Analysis. *Transportation Research Record: Journal of the Transportation Research Board*(2481), 1-9.

Zhu, J. (2014). *Data Envelopment Analysis: Let the Data Speak for Themselves*: CreateSpace Independent Publishing.