MANPOWER AND EFFICIENCY STUDY OF THE MANNS HARBOR SHIPYARD THROUGH DATA ENVELOPMENT ANALYSIS

by

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ABSTRACT

TYLER K. MORGAN. Manpower and Efficiency Study of the Manns Harbor Shipyard through Data Envelopment Analysis. (Under the direction of DR. OMIDREZA SHOGHLI)

The NCDOT Ferry Division (NCDOT-FD) self-performs preventative maintenance, emergency maintenance, and scheduled overhauls on a continual basis with manpower staffing to support the North Carolina Ferry Service's (NCFS) ability to continue to operate and provide the high level of services provided to North Carolinians and visitors to the state's east coast. 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 is to measure and evaluate the efficiencies of the NCDOT-FD maintenance and repair operations using Data Envelopment Analysis (DEA). The use of DEA allows for multiple factors affecting maintenance productivity to be accounted for and allows the sources of inefficiencies in maintenance operations to be identified through examination of efficient or "best practice" DMUs. Results presented in this study are used to develop an overall strategic plan for enhanced decision-making with regards to labor and resource requirements, maintenance scheduling, and management strategies for the NCDOT-FD. Inefficient maintenance operations are identified through DEA evaluation, and recommendations for increased efficiency and productivity of these operations are provided through analysis of several quantitative and qualitative factors. Additionally, performance benchmarks provided in this paper can be used as an early warning system for inefficient shipyard maintenance operations. The use of quantified factors in the development of an overall strategic plan for manpower needs may be used for both short and long-term planning

to provide an analytical approach for what is typically subjective judgement in determination of staffing and scheduling needs, organizational structure, and performance targets.

DEDICATION

First, I would like to dedicate this thesis to both my maternal and paternal grandparents Becky, Don, Dianne, and Foy. Although they are no longer with us, they all played an integral part in shaping me into the man I am today. I cannot thank them enough for the love and care they provided and the everlasting memories we shared together. The invaluable values and lessons they taught me will stay with me forever.

Next, I would like to dedicate this thesis to my late best friend Devin. This world took you away at the young age of 13. However, the time we spent together whether on the baseball field or just being kids is something I will cherish forever. Despite being so young, you will always be someone that I look up to and you were truly one of the best individuals I have ever met. I will always remember “God don’t like ugly.” I cannot wait until we meet again someday.

Finally yet most importantly, I would like to dedicate this thesis to my parents Debbie and Keith and my “little” brother Timothy. Thank you for your continuous love and support throughout my life. Without you guys I would not be in the position I am today. You all taught me the true meaning of hard work and dedication by setting an example throughout my life.

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Lastly, I would like to acknowledge the North Carolina Department of Transportation (NCDOT) for providing the funding to make this research possible. I would also like to specifically thank all of the employees at Manns Harbor shipyard for their assistance throughout the project. In addition to the Manns Harbor, I would also like to thank the four additional shipyards that provided valuable information and research data for this study.

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CHAPTER 1: INTRODUCTION

Information provided by ferry operators participating in the 2014 NCFO survey shows that U.S. ferries carried over 115 million passengers and just over 30 million vehicles in the year 2013 (Steve et al., 2016). In the South, there were 26.4 million passengers served followed by the Midwest with approximately 10.4 million passengers. The importance of maintaining assets for the NCDOT Ferry Division (NCDOT-FD) directly influences the services provided to millions of passengers each year. Although the Manns Harbor (North Carolina State) shipyard is the largest state-operated shipyard in the U.S., the number of personnel at that operation has decreased. The current number of personnel for the shipyard has reduced from previous years to now 65 employees (Stegall, 2017). Coast Guard polices require all ferries to be dry-docked twice every five (5) years for maintenance, repair, and inspection. However, with augmented ridership, aging vessels, and annually deteriorating channel conditions, the maintenance levels for ferry vessels require increasingly more attention, which has an effect on the planned manpower staffing needs, resource requirements, and dry-docking schedules. 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. Forecasting upcoming needs is a good business practice and assists with planning to minimize these effects. This is especially important in the maritime maintenance and repair industry where the majority of operations are heavily dependent on skilled trades and manual labor. Efficient operations, increased productivity, and effective management strategies are critical to the vitality of ship repair facilities, where time is of the essence in many cases.

To effectively study manpower for any operation, there is a need to understand efficiency, which is a nebulous concept that pertains to the ideal levels of productivity. Productivity is the ratio of output to input. For example, "Employees who seem to work the least can be the most productive. Business units that boast high profitability can sometimes be the least efficient" (Cook & Zhu, 2013). To accurately evaluate the efficiency of an operation, all factors potentially affecting productivity and the production process must be taken into account. Therefore, manpower studies can be difficult because of the vast number of variables affecting production and productivity. From a general approach, if a worker produces twice as many units or performs the same service in one-half the time, it can be said that his or her productivity has doubled, but this does not account for quality and other important considerations. Determining efficiency is also more challenging for public agencies, who have typically struggled with the concept. In the public service industry, productivity is the effectiveness with which resources are consumed throughout the delivery of a service. 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 ever more challenging. Factors affecting productivity are not always directly related to the production process, which makes the identification of these variables an extensive task. Productivity can be influenced by production processes, management strategies, organizational structure, environmental elements, and geographical constraints, as well as many other internal and external factors (Rabar, 2015). Therefore, the maintenance and repair process must be investigated thoroughly and understood fully so that variables selected for efficiency evaluation of the NCDOT-FD are inclusive of all factors affecting productivity.

Traditional approaches to measuring shipyard productivity have included generic calculations, which have weaknesses because they provide little insight into the causes of productivity changes. Other methods generate very detailed measures that make it difficult to draw the needed conclusions for operational decisions. Many efforts concerning efficiency are used to review individual or group productivity levels using a single input/single output method. 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 that it has been charged to produce. These "outputs" can also be service-related as opposed to a manufactured part. This advantage in DEA is beneficial as an analysis for determining efficiency and manpower for the NCFS 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.

The purpose of this research is to develop a methodology that can be used by the NCDOT-FD and other ship maintenance facilities as a tool for benchmarking and forecasting, as well as strategic, operational, and tactical planning. DEA was utilized as a method of evaluating the efficiency of maintenance and repair operations, analyzing the causes of inefficient operations, and determination of potential corrective action. The most significant contribution provided by this analysis is the use of the procedures described and outlined in this report as an analytical means of determining organizational structure, manpower staffing requirements, and optimal shipyard maintenance schedules. Continuous improvement in any application requires constant changes to operations and procedures. However, from first hand observation many industries and businesses, especially those concerned with marine maintenance and repair, have a resistance to change. When combined with poor management strategies, many times these businesses become stagnant and unchanging which leads to less than optimal performance. The significance found in this research stems from the ability to evaluate marine maintenance and repair operations and determine corrective action in cases of inefficiency. In order to remain competitive in the ship repair industry and on course with the ever-increasing productivity of maintenance and repair facilities, continuous improvement strategies must be implemented into the planning strategies of these facilities. This research is aimed at developing a methodology for use in planning day-to-day operations as well as a continuous improvement tool for ship repair facilities.

CHAPTER 2: LITERATURE REVIEW

2.1 - Efficiency and Productivity

As previously mentioned, understanding efficiency and productivity is crucial to effectively studying manpower. At the most basic level, productivity can be defined as the ratio of output to input (Lamartin, 1980). Inputs can be understood as the resources used to produce an output, which can be a product or service. Therefore, optimal productivity can be understood as producing the greatest possible amount of output using the least amount of input. While productivity may seem rather easy to understand, there are several insinuations that have caused confusion surrounding the term (Tangen, 2002). One of the most common faults surrounding productivity, is the use of the term synonymously with the term production, which refers to the amount of a product or service produced (Tangen, 2002). As a result of this, Tangen (2002) states that people tend to relate an increase in production with an increase in productivity, which is not necessarily true because productivity is a relative concept and cannot be said to increase or decrease unless comparison is made between two time periods, entities, or other standards. However, there are five basic ways that productivity can be increased: (1) output and input increases, where the increase in input is proportionally less than the increase in output; (2) output increases while input stays the same; (3) output increases while input is reduced; (4) output stays the same while input decreases; and (5) output decreases while input decreases even more (Tangen, 2002). To further eliminate confusion surrounding productivity, there is a need to understand the different types of productivity. The two types are partial productivity and total productivity. Partial productivity is understood to be output related to one type of input while total productivity is output related to multiple types of input (Tangen, 2002). For example, in ferry maintenance, partial productivity would be looking at the productivity of an individual trade (single input) that performs ferry maintenance while total productivity would be the productivity of all the trades (multiple inputs) that perform maintenance. The ability to distinguish between the two is vital to understanding the concept of productivity.

In realistic applications, this basic ratio of output to input does not take into account many of the additional factors that affect productivity. Rabar (2015) suggests that productivity measures are partial when based on single indicators because they are not inclusive of all factors which affect production. Furthermore, it has been stated that the efficiency of a shipyard operation is comprehensively affected by the mix of management, technology, and production activities. Inputs used for evaluation of productivity must include resources used as well as general production influencers to accurately determine production efficiency. Earlier studies and research have transformed the definition of productivity to include these factors. In a work study on the relationships between productivity and efficiency, Al-Darrab (2000) defines productivity as the ratio of output to input multiplied by a quality factor, he goes on to further define productivity as the product of quality, utilization, and efficiency. Pires and Lamb (2008) suggest production influencers include the industrial environment of the region, technology levels, and output pattern characteristics such as the types of products produced, and the production processes used. Additionally, theses definitions, applied to this study, indicate that technological and managerial capabilities are important influencers of competitiveness for a shipyard.

Understanding that there are numerous factors in the determination of productivity is essential when conducting studies on manpower. Traditionally, productivity measurement has been interpreted as the process of identifying and comparing an output to input ratio over two or more periods of time (Lamartin, 1980). While this process may seem straight-forward in many cases, in public entities and other service industries, this process is more complex due to the nature of production. Service industries provide a service to their customers and productivity in these industries is measured by the resources consumed to provide service to a customer. Generally speaking, the primary resource used to provide services is manpower. The problem arises when trying to quantify the amount of manpower required to provide a service. While using pure man-hours as the input to a service makes logical sense, using only time as an input does not take into account the many aforementioned production influencers that may affect manpower productivity. Additionally, in service industries quantification of output is also much more complex. Because of this, measurement of production efficiency in service industries requires detailed investigation into the production operations and thorough understanding of the factors related to production.

Efficiency is an ambiguous concept used to develop a theoretically ideal productivity situation. Abdullah et al. (2012) stated that the theory of efficiency is related to the association between resources used and results achieved. In other words, efficiency is strongly related to the utilization of resources and mainly influences the input of the productivity ratio (Tangen, 2002). In more simplistic terms, efficiency can be understood as how well an input of a process is utilized. Tangen (2002) defines efficiency in manufacturing as the minimum resource level that is theoretically required to run the desired operations, compared to the quantity of resources actually used. Efficiency can be used in a manpower study to compare how productive one operation is to another. Al-Darrab (2000), when comparing labor productivity, defines efficiency as a ratio of standard hours to actual worked hours. Efficiency measurement is a key concept to companies, organizations, firms, or facility operations that struggle with measuring their own productivity and efficiency (Shirouyehzad et al., 2012) . To analyze efficiency in any operation, the first step is to begin by developing a simple equation that relates productivity with efficiency and utilization (Al-Darrab, 2000). However, the problem with developing this equation comes when there are multiple inputs and outputs to be analyzed. The reason for the majority of failure in terms of measuring efficiency stems from the failure to combine the measurements of multiple inputs and outputs as well as unjustified combination of multiple inputs and outputs (Cook & Seiford, 2009; Shirouyehzad et al., 2012).

2.1.1 - Previously Developed Methods and Approaches

Performance measurement, as defined by Neely et al. (1995), "is the process of quantifying action, where measurement is the process of quantification and action leads to performance." A performance measure is defined as a metric used to quantify the efficiency and/or effectiveness of an action and a performance measurement system can be defined as the set of metrics used to quantify the efficiency and effectiveness of an action (Neely et al., 1995). Performance of an operation or entity can be defined in many ways (Coelli et al., 2005). Productivity ratio is a natural measure of performance in many instances. Conversely, Coelli et al. (2005) stated that performance is a relative concept. For example, the performance of a shipyard in the current year (in terms of productivity) can be measured relative to the performance of the shipyard in previous years or it can be measured relative to the performance of other shipyards. Moreover, Al-Darrab (2000) expresses that measures of performance include productivity, efficiency, utilization, and quality. For the purpose of this research however, only productivity and efficiency will be used as performance measures.

Productivity measurement, historically, has been used for many diverse purposes. One of the most significant uses of productivity measurement has been to benchmark and track performance over time. Benchmarking is good business practice and has been the customary way for many businesses to determine and measure their performance. Additionally, benchmarking allows for the establishment of performance targets. Rabar (2015) suggests that production benchmarks establish an early warning system for inefficient operations. Moreover, establishing targets creates a sense of accountability for reaching these goals and allows for continuous improvement and increased productivity through continual monitoring of production operations.

Throughout earlier studies and research there have been many unique methodologies and techniques employed to measure efficiency and productivity in various operations. Quantifying performance is important when making decisions. Performance measurement metrics enable entities to determine poor performance, identify and mitigate root causes of poor performance, and monitor improvement over time (Abdullah et al., 2012). Two approaches to measuring performance are parametric and non-parametric. Abdullah et al. (2012) explain that parametric approaches require functional form and account for residual term during analysis and non-parametric approaches require less structure and do not assume random error. The main difference between the two approaches is in terms of data distribution, parametric approaches are concerned with the normality of the distribution while non-parametric approaches do not (Abdullah et al., 2012). Non-parametric approaches have many advantages when compared to parametric approaches. Benefits of non-parametric approaches are simplicity, effects of outliers are less significant, consideration of data set relationships is not required, assumptions about data is not required, and generally non-parametric methods can be used in a more comprehensive range of data (Abdullah et al., 2012).

In routine operations, businesses use and count on a number of performance measurement methods related to productivity and efficiency measurement including but not restricted to key performance indicators, input/output analysis, balanced scorecard, and data envelopment analysis (Bröchner, 2017). Cook and Seiford (2009) acknowledged other approaches to measuring efficiency, which involved finding an average productivity for a single input and devising an efficiency index where a weighted average of inputs is compared to output. Yet, this method ignored all other inputs and focused only on one single input. Farrell (1957) fashioned an activity analysis approach that would more sufficiently quantify efficiency and productivity. Farrell's method was intended to be pertinent to any productive organization, however he restricted his discussions to single output cases (Cook & Seiford, 2009).

To measure productivity and efficiency in the healthcare industry, Al-Darrab (2000) developed a methodology that related productivity to efficiency, utilization, and quality. The data used in this method was associated specifically to labor productivity and included worked man-hours, required man-hours and actual worked man-hours. This method developed equations to determine productivity, utilization, and efficiency and the results were used to produce numerous production level curves. A productivity index was used to establish manpower productivity levels by dividing earned man-hours by worked man-hours. Using this index, Al-Darrab was able to define optimal productivity, a value greater than 100 percent indicated greater productivity than expected and a value of less than 100 percent showed less than optimal productivity (Al-Darrab, 2000). This method, like many others, only uses a single input/output method to determine efficiency and productivity limiting the areas to which it is applicable.

Deng, Smyth, and Anvuur (2013), reviewed performance measurement systems in construction firms across the world. Throughout a greater part of the research, Deng et al. (2013) determined the majority of performance measurements in the construction industry were related to key performance indicators (KPI). It was concluded there are two main types of performance measurement systems used in construction. The first includes those that only focus on identifying KPIs and the second are those that focus on identifying KPIs as well as delivering benchmarking tools (Deng et al., 2013). Nevertheless, these methods only provide indicators to help improve performance; they do not provide an objective solution in defining efficiency or productivity.

While many of these methods are applicable in many situations, they do not offer a means for performance measurement in all instances. The aforementioned methodologies and approaches have considerable limitations and do not provide a means for efficiency and productivity analysis when multiple inputs and outputs need to be considered or if there are uncontrollable factors that play a significant role in productivity. Efficiency cannot be measured explicitly using traditional methods when multiple input/output factors are involved and cannot be directly added together (Zhang, Agbelie, & Labi, 2015). Conversely, a method generated by Charnes, Cooper, and Rhodes (1978), Data Envelopment Analysis (DEA), can be used to measure technical efficiency and productivity in multiple input/output cases. DEA, its methodologies, types, and practices are described in detail in the subsequent section of this document.

2.2 - Data Envelopment Analysis (DEA)

2.2.1 - Multiple Input and Output Methods

Data Envelopment Analysis uses the measurements of the efficiencies instances where there are multiple inputs and/or outputs. Ozbek et al. (2010) identified the five approaches that can be used to measure and compare the efficiencies of processes with multiple inputs/outputs. These five identified approaches are the partial efficiency measure approach; the total factor efficiency approach; system dynamics; regression analysis; and DEA (Ozbek et al., 2010). A brief discussion of the first four previously listed approaches as well as the advantages and/or disadvantages to each will be provided in the following paragraphs. DEA is explained in detail in the following section.

The partial efficiency measure approach requires calculating the single output to input ratio, one at a time, for each relevant input and output (Ozbek et al., 2010). Though this process may be used to determine the overall efficiency, it has the potential to produce inaccuracies and misunderstandings in relation to its results. One of the major downsides to this approach is that it is exceptionally challenging for decision makers to make definitive conclusions about the overall efficiency of a process when compared to the efficiency of other processes, even if all of the possible partial efficiency ratios are computed for that process (Ozbek et al., 2010). The total factor efficiency approach determines efficiencies by deriving an output-to-input measure that accounts for all of the inputs and outputs at one time (Ozbek et al., 2010). While this solves the problem encountered with the partial efficiency measure approach, Ozbek et al. (2010) state that the disadvantage to this approach is that it requires the user to prescribe weights to each input and output variable to obtain a ratio that can be simplified to the basic output to input ratio.

The third approach capable of analyzing multiple inputs/outputs is system dynamics. This approach is used to understand, model, and simulate the dynamic behavior of complex systems (Ozbek et al., 2010). System dynamics models a problem that establishes itself over time by capturing feedback mechanisms (Ozbek et al., 2010). Advantages and disadvantages of this model have been identified throughout literature, such as by Ozbek et al. (2010) who identified the major advantage as its ability to capture temporal impacts of decisions and the major disadvantage as the requirement of definition of structure for the process being analyzed. The fourth approach for multiple inputs/output cases is regression analysis. This approach suggests that a parametric equation for efficiency that relates inputs and outputs can be developed by performing regression analysis on input/output data under investigation (Ozbek et al., 2010). This main disadvantage to this approach is due to the fact that it compares efficiency of units to a hypothetical average performance from the developed equation rather than the best performers (Ozbek et al., 2010). Due to the shortcoming of the aforementioned approaches, DEA has been identified as the best approach for the study of efficiency and manpower in relation to shipyards and shipyard maintenance.

2.2.2 - Basics of DEA

The DEA method was first established for the purpose of establishing an estimate of technical efficiency by Charnes et al. (1978). From a technical viewpoint, DEA is termed a non-parametric optimization method of mathematical programming (Bröchner, 2017; Monika & Mariana, 2015; Shirouyehzad et al., 2012). Technical efficiency is understood to be the ratio of minimum possible input, given a fixed output level, to actual input required (Carnes, Hunn, & Jones, 1998). Efficiency and process flow may be analyzed by DEA because it is used to measure efficiency when there are multiple inputs and outputs and there are no generally acceptable weights for aggregating those inputs and outputs. DEA allows for these variations – as opposed to attempting to associate a unit's performance with statistical averages. Often, these averages may not be applicable to that particular unit's operations (Gökşen, Doğan, & Özkarabacak, 2015).

DEA applications have since been used to evaluate the efficiency of decision-making units (DMUs) for entities like cities, courts, universities, business firms and hospitals. Determination of ideal performance within an entity is often impossible. The advantage of DEA is that efficiencies are observed as comparisons between entities or selected DMUs rather than comparison using a theoretical ideal performance measurement (Carnes et al., 1998). After analysis, the resulting information by DEA establishes what is called an "efficiency frontier" consisting of many linear combinations of efficient producing units. Those producing units not in the frontier are said to be inefficient. The inefficiency can be described through the variables selected and may also provide an indication as to why there are certain inefficiencies based on the selected input and output variables. DEA essentially calculates the economic efficiency of a given utility relative to the performance of other utilities producing the same sorts of services, rather than against an idealized standard of benchmarked performance. Cook and Zhu (2013) coined the term “balanced benchmarking” as a description of the DEA method because it generates a composite measure based on the best scenario. For example, as opposed to finding the central tendency for a data set and trying to fit a regression plan through the center of the data, DEA applies a piecewise linear surface over the observations. A distinct advantage is that it enables a view of potential improvements (that are not at the expense of other metrics) and uncovers relationships that may not have been apparent with fitted data. Moreover, each DMU is viewed as a possible benchmark for improvement, as opposed to attempting to fit with what is considered a normal level of efficiency (Zhu, 2014). The purpose of benchmarking is to provide a “best practices” metric with regards to other similar services (shipyards in this case). Benchmarked information will enable the researchers to utilize existing industry practices to apply operations metrics for other ferry services to the analysis.

2.2.3 - DEA Models

Since the advent of DEA by Charnes et al. (1978) there has been tremendous advancement around DEA in terms of theoretical developments and useful applications (Cook & Seiford, 2009). Due to this evolution of DEA, many new models and methodologies have been established and implemented by both researchers and practitioners. While the purpose of this paper is not to discuss the entirety of all the numerous models in detail, the three basic types of DEA models are envelopment models, multiplier models, and additive or slack-based models (Cook & Zhu, 2013). Of the three basic model types, envelopment models were the first developed, the most simplistic in nature, and provided a foundation for future model development. Multiplier and additive models use the same fundamental process as envelopment models. However, the main differences between the basic envelopment models and multiplier or additive models are the procedures to calculate technical efficiency, the use of additional constraints, and the means of assessing inefficiencies. Along with these basic models, other models include super efficiency, Malmquist Index, the Russell measure, the free disposal Hull model, the Andersen-Petersen model, as well as many various multilevel models (Cook & Seiford, 2009). Of these abovementioned models, only the three basic model types will be discussed further as many of the multilevel models are intended for specific applications not relevant to this research.

Envelopment models are used to establish a best-practice frontier and get their name because the best-practice frontier produced from the model envelops all referenced DMUs (Cook & Zhu, 2013). The two most basic types of envelopment models are the CCR model and the BCC model. The CCR model was the first DEA model, originally developed by Charnes et al. (1978); it is also one of the most basic DEA models. The BCC model was crafted by Banker et al. (1984) as an extension of the initial work of Charnes et al. (1978); (Cook & Seiford, 2009). 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). Because of this discrepancy, 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 surface created by the CCR model assumes that an increase in inputs results in a proportional increase in outputs (McCabe, Tran, & Ramani, 2005). The surface established by the BCC model encases the data by connecting the outermost DMUs including the one approached by the CCR model. Using the BCC model allows for an increase in input values to result in a non-proportional increase in output levels (McCabe et al., 2005). In actuality, a CRS is a rather ideal assumption that does not occur often, therefore a VRS is normally chosen more often (Zhang et al., 2015). A visual representation of the differences between the two models can be seen in Figure 1. Further discussion of returns-to-scale (RTS) and the types are provided later in this section.

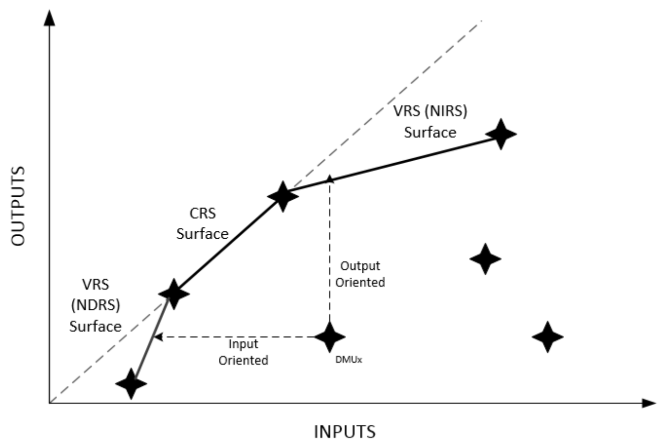

Figure 1: Surface and Orientation

Multiplier models are very similar in nature to the basic envelopment models. The main difference being the way efficiency is measured. In the basic envelopment models, the efficient frontier is developed through radial projection and it is assumed that all inputs (or outputs) undergo a proportional increase or decrease when evaluating inefficient DMUs (Cook & Zhu, 2013). Multiplier models on the other hand, introduce an additional element to the basic envelopment models. In multiplier models, input and output variables are weighted based off importance or other various factors, and efficiency is evaluated as the ratio of weighted outputs to weighted inputs (Cook & Zhu, 2013). Multiplier models can be very valuable in real-world applications where multiple factors, both internal and external, can affect production in varying degrees. Additive or slack-based models, like multiplier models, are much the same as envelopment models with the main difference being the evaluation of inefficient DMUs. In envelopment models, the assumption is made that an increase or decrease in inputs results in a proportional increase or decrease of output. Therefore, in envelopment models inefficiencies are evaluated off this assumption or the efficiency scores produced by the model (Cook & Zhu, 2013). For additive models, this assumption is not present which makes the evaluation of inefficiencies much different. In additive models, inefficiencies are evaluated by reducing inputs and increasing outputs (or vice versa) at different proportions to determine the source of inefficiencies (Cook & Zhu, 2013).

While there are differentiations between models, the fundamental process for carrying out Data Envelopment Analysis does not change on a model-to-model basis. Models should be selected on a case-to-case basis based on the application and anticipated outcomes or goals of the analysis. Once a DEA model has been selected, an orientation of the model must be determined. Orientation is a vital aspect of DEA models. Orientation specifies the direction in which an inefficient DMU approaches the efficient frontier (McCabe et al., 2005). Models can be either input-oriented or output oriented. Input-oriented models accentuate the use of minimal input resources to attain a known output level (Abdullah et al., 2012). Output-oriented models place emphasis on achieving maximum possible output using a given set of inputs (Abdullah et al., 2012). In other words, an input-oriented model is concerned with reducing inputs and maintaining current output levels, while an output-oriented model is focused on maximizing output given current input levels. A graphical depiction of output and input orientation can been seen in Figure 1. Relative efficiencies can be measured using either orientation however; the efficiency score range is dependent on the type of orientation. The range of efficiencies for input-oriented models is from 0 to 1.0 and for output-oriented models the range is from 1.0 to infinity (Abdullah et al., 2012). In either case, a score of 1.0 is considered efficient.

Additionally, when selecting a DEA model, the type of returns-to-scale (RTS) used is a major factor and knowledge of the production frontiers of the process to be analyzed is crucial (Rabar, 2015). RTS refers to the increasing rates of output when inputs are increased proportionately (Ok & Feng, 2017). The two main types of RTS used in DEA models are the constant-returns-to-scale (CRS) and the variable-returns-to-scale (VRS). The CRS assumes changes to input results in a proportional change to output. A linear frontier is produced using a CRS, and only DMUs that fall on the frontier are considered efficient. While simplistic in nature, often times the efficient frontier produced by the CRS does not represent realistic conditions. This is due to the fact that, in actuality inputs and outputs very seldom change proportionally. This limitation was overcome by Banker et al. (1984) through the development of the BCC or VRS model. The VRS surface is made up of three individual elements: the CRS surface, the non-increasing-returns-to-scale (NIRS) surface, and the non-decreasing-returns-to-scale (NDRS). The VRS surface is developed by connecting the two outermost DMUs on the efficient frontier with the CRS surface, which can be seen in Figure 1. The VRS surface allows for increases in inputs to result in non-proportional increases to outputs, or in other words, the VRS better estimates actual conditions (in most cases) rather than making an assumption of proportionality between inputs and outputs. As previously stated, selecting the correct RTS for analysis is dependent on the specific application area under investigation and the production characteristics of that industry. Knowledge of production frontiers comes from historical data analysis and experts in the particular application. In a manufacturing setting, understanding production trends is much more forthright than the production trends of a service provider because the amount of resources (inputs) required to produce a product (output) is a known, trackable variable. In a service industry such as a ship repair facility for example, understanding production frontiers is not as straightforward because the facility provides a service instead of a product. Unlike the repetitive cycle of manufacturing, ship repair services do not remain constant from vessel to vessel. Therefore, the levels of service, maintenance requirements, ship geometry, and ship operational systems vary from project to project. As a result, production patterns can vary drastically from project to project making them difficult to predict or standardize. While this is just one example, determining production patterns requires detailed knowledge of the area under investigation regardless of industry and in many cases cannot be accurately determined. In cases where an RTS type cannot be determined with certainty, literature suggests that the analysis should be carried out using both CRS and VRS (Ok & Feng, 2017; Rabar, 2015). Performing the analysis using both RTS forms allows the RTS that best represents the production frontier to be identified and ensures the accuracy of the analysis. In addition to these benefits, execution of DEA using a CRS and VRS permits the calculation and comparison of multiple different type of inefficiencies (Rabar, 2015). Therefore, it can be said that regardless of industry or production knowledge, performing DEA with both RTS can provide additional benefits and redundancy, while providing potentially more accurate determination of the sources of inefficiencies.

When comparing DEA to traditional performance measurement practices several advantages are realized. Some of these benefits have been discussed in prior sections of this document. These previously conversed advantages are the proficiency in handling multiple inputs and outputs, efficiencies are reflected as comparisons between DMUs, and DEA assists in distinguishing potential improvements while bringing to light relationships not professed in former methods. Zhang et al. (2015) pinpoint that advantages to DEA are its flexibility, its capability of handling any type of input or output, and its ability to use data sets that do not encompass a common unit of measurement. Moreover, DEA provides objectivity to efficiency scores and can evaluate external and uncontrollable factors in the analysis (Ozbek, 2007). Along with advantages, there are also limitations to DEA. Ozbek (2007) states that DEA is a non-parametric method therefore statistical tests are not capable of easily evaluating the validity of results making the results very subjective in many instances. Ozbek (2007) goes on to state other confines include inaccuracies in input and output variables have the potential to cause substantial problems and that DEA is difficult to explain to non-technical audiences because it uses a series of linear programming formulations to determine efficiency scores (Ozbek, 2007). Basic DEA models are also not capable of handling negative numbers, consequently all data must be non-negative (Sarkis, 2007).

2.2.4 - Selection of Inputs/Output Variables and DMUs

The applications and use of Data Envelopment Analysis depend heavily on the data used as inputs and outputs (Sarkis, 2007). The discriminatory power of DEA is reliant on the inputs, outputs, and number of DMUs (Sarkis, 2007). Carnes et al. (1998) assert that the fewer inputs and outputs, the better the discrimination generated. When determining data sets for DEA, multiple contemplations need to be made. The primary and most imperative criteria when selecting data is homogeneity among DMUs (Zhang et al., 2015). When looking at the homogeneousness among DMUs, the three most important considerations are (a) performing similar tasks with similar objectives, (b) similar market conditions, and (c) the use of similar technology (Zhang et al., 2015). Carnes et al. (1998) further illuminate this by declaring that DEA is only fitting for assessment of facilities involved in similar activities.

In literature focused on DEA, the number of DMUs along with the number of variables to use for input and output for accurate analysis has been a topic of abundant discussion. Many of the recommendations provided from prior research contain conflicting considerations. One suggestion is to include as many DMUs as possible as there is a larger probability of capturing high performance units which determine the efficient frontier (Sarkis, 2007). However, the contradictory consideration to be made when a large quantity of DMUs are used is the potential for a significant decrease in homogeneity across the data set. When homogeneity is decreased, uncontrollable exogenous factors have a greater chance of affecting the results of the analysis (Sarkis, 2007). While there is not an exact solution for determining the appropriate data set for accurate analysis using DEA, over the years, researchers and DEA specialists have created several rules of thumb to follow when selecting data.

Sarkis (2007) identified these generally accepted rules of thumb in his publication about the preparation of data for DEA citing authors such as Golany and Roll (1989) who were the first to establish a rule of thumb concerning data selection for DEA. They suggested the number of DMUs should be two times the number inputs and outputs. Bowlin (1998) proposed there should be three times the number of inputs and outputs. Boussofiane, Dyson, and Thanassoulis (1991) advised the minimum number of DMUs should be the product of inputs and outputs and Dyson et al. (2001) mentioned the number of DMUs should equal twice the product of inputs and outputs. For example, in a case where there are two inputs and four outputs, Golany and Roll (1989) recommend a minimum of 12 DMUs, Bowlin (1998) recommends 18, Boussofiane et al. (1991) recommend 8, and Dyson et al. (2001) recommend 16. In spite of the fact these rules were developed to assist with data selection, in most circumstances they should be used as minimums for basic productivity models (Sarkis, 2007). The rule of thumb used by analysts in prior DEA is dependent on their personal preference. Abdullah et al. (2012), McCabe et al. (2005), and Marchetti and Wanke (2016) all suggest the use of the recommendation set forth by Bowlin (1998). Zhang et al. (2015) and Ozbek et al. (2010) use the rule suggested by Dyson et al. (2001) while Carnes et al. (1998) suggest following the rule of thumb introduced by Boussofiane et al. (1991). There is no consensus on which rule of thumb provides the best discrimination during analysis.

The previously cited rules are thumb are helpful in the majority of DEA uses, however there are many occasions where the number of DMUs available for study can be relatively small. For instance, the extent of DMUs available for efficiency evaluation of ferry maintenance operations is constrained because of the infinitesimal number of shipyards concerned with ferry maintenance and repair willing to share operational information. To accommodate the loss of discriminatory power due to the lesser number of DMUs, specialized variations of traditional DEA models have been established. These specialized models, referred to as super efficiency models, have the capability to discriminate amongst DMUs regardless of data set size (Cook & Seiford, 2009; Sarkis, 2007). The development of these models has expanded the realm to which DEA is applicable. As an alternative to super efficiency models, other methods to increase the quantity of DMUs have also been developed for use in basic DEA model applications. Of the alternative methods, time series application of DEA, or more commonly referred to as window analysis, is the most pertinent in terms of this research and has been used in various practical and service related applications (Al-Refaie, Hammad, & Li, 2016; Asmild, Paradi, Aggarwall, & Schaffnit, 2004; Charnes, Clark, Cooper, & Golany, 1984; Pjevčević, Radonjić, Hrle, & Čolić, 2012; Rabar, 2015; Yang & Chang, 2009).

Originally implemented by Charnes et al. (1984), window analysis has proven to be valuable in many practical applications where the data available for use in efficiency evaluation are from different time periods; e.g. yearly, quarterly, monthly, etc. (Al-Refaie et al., 2016; Asmild et al., 2004; Charnes et al., 1984; Pjevčević et al., 2012; Rabar, 2015; Yang & Chang, 2009). Window analysis is an application of DEA in a time series mode that generalizes the notion of moving averages to detect efficiency trends of DMUs over time (Yang & Chang, 2009). In terms of discriminatory power, window analysis increases the discriminatory power of the model by increasing the number of DMUs available for evaluation (Pjevčević et al., 2012; Yang & Chang, 2009). The rationale behind window analysis is that each DMU in a window or period is regarded as an entirely different one, effectively increasing the number of units available for evaluation. For example, if five DMUs are being evaluated and the available data is over a five-year period (assuming each year is a different window), application of window analysis would increase the number of DMUs to 25 because each DMU per period is evaluated independently. Furthermore, the performance of each DMU is compared with its performance in other periods of time and with the other DMUs in the same time period. Application of window analysis also provides several additional benefits when compared to traditional DEA applications. The main advantage is that window analysis allows for determination, observation, and evaluation of efficiency changes over time. Moreover, the results of window analysis can serve as an early warning system for inefficient DMUs (Rabar, 2015). Additionally, another distinct advantage provided by window analysis is that the length of each window can be selected by the practitioner conducting the analysis (Pjevčević et al., 2012). Despite the notion that window length can be chosen freely, it has been pointed out that the window should be as small as possible to ensure the technological change within each window is negligible, but large enough to maintain a sufficient sample size for adequate discriminatory power (Asmild et al., 2004; Yang & Chang, 2009).

Along with the selection of DMUs, the selection of variables used as inputs and outputs is equally important to the discriminatory power of DEA. DEA is profoundly reliant on the data used; meaning correct application requires proper selection of input and output variables. In DEA, all variables have an equal opportunity to influence efficiency outcomes because no former distinction is made regarding the relative importance of one variable compared to another (Zhang et al., 2015). Therefore, including too many variables into a model has the potential to reduce discriminatory power, especially when the number of DMUs is relatively small (Sarkis, 2007). A large quantity of DMUs will have high efficiency scores when too many variables have been included (Zhang et al., 2015). Generally, smaller quantities of inputs and outputs produce better discrimination. Across the review of numerous publications concerning DEA, the number of inputs and outputs used tend to be relatively small and more often than not are limited to five or less. Because of this, only the most pertinent and relevant variables related to production should be selected. Likewise, Rabar (2015) suggests that the most important criterion for variable selection is to ensure the variables selected will provide relevant and useful information to management, owners, and other personnel concerned with production or performance decisions. In instances where numerous variables are being considered, examination of the correlation amidst the variables will identify redundancy and support with eradicating unnecessary variables (Lamartin, 1980).

2.2.5 - Historical Approaches and Uses of DEA

Department of Transportation (DOT) research has reported various uses of DEA to determine efficiencies (Jalili, 2015); Ozbek (2007); Ozbek, de la Garza, and Triantis (2009); Ozbek et al. (2010); (Zhang et al., 2015). In his doctoral dissertation, Ozbek (2007) performed one of the initial comprehensive studies on the application of DEA to the transportation industry. Ozbek (2007) researched the use of DEA as a comprehensive efficiency measurement framework of highway maintenance for the Virginia DOT. To conduct his study, Ozbek (2007) used an input-oriented BCC model that included eight DMUs, three inputs, and one output. Since this initial study, the application of DEA in transportation applications has been further researched by Ozbek and others. Ozbek et al. (2009) investigated the use of DEA in DOT applications and provided an analysis on its use for transportation professionals. Ozbek et al. (2010) furthered exploration surrounding these applications by identifying common issues faced during DEA applications for road maintenance and provided guidance for mitigating those issues. Additionally, during the research (Ozbek et al., 2009) outlined the steps to generate a DEA model. Their steps and subsequent notable explanations include:

<u>Phase 1 - Definition and Selection of Decision-Making Units to be used.</u>

- Input/output variables should be identical and units to be considered should be for similar objectives and operating in a similar environment. Also, the larger the population of the data set, the larger the probability of capturing high performance DMUs that would form the efficient frontier.

<u>Phase 2 - Definition, Selection, and Measurement of Input and Output Variables</u>

- There is no prior distinction made between the input/output results so any variable may equally influence the calculated efficiency. Additionally, using a number of variables will shift the DMUs because as DEA allows flexibility in the choices and weights, the greater the number of variables, the lower its level of discrimination. It is recommended to use 2*m*t where m*t is the product of the number of inputs and outputs (Dyson et al., 2001).

<u>Phase 3 - Selection of the Data Envelopment Analysis Model and Formulation</u>

- The article outlines sub-steps of this phase to state that first, if the data set are experiencing variable returns to scale, the use of the Banker, Charnes and Cooper (BCC) model can be used to account for scale inefficiencies. If not, the Charnes, Cooper, Rhodes (CCR) model should be used. Secondly, the decision should be made to identify whether to use and input-oriented or output-oriented model depending on the decision maker's interest and goals.

Phase 4 - Application of DEA Models

- It is recommended that an appropriate software specifically designed for DEA analysis be used.

Phase 5 - Post data Envelopment Analysis Procedures

- Because DEA is a nonparametric method, it is not possible to estimate the confidence levels as used in general statistical methods. The DEA results should be viewed with caution and consideration should be taken to conduct sensitivity analyses – for example, removing the efficient DMUs and reviewing again.

Phase 6 - Presentation and Analysis of Results

- "The DEA results are intended to be used as guidelines for managerial actions and policymaking as calculated targets for inputs and outputs indicate potential performance and efficiency increases for inefficient DMUs." For this reason, DEA results should be presented in a very concise way, possibly with the use of some charts and easy to follow tables.

Zhang et al. (2015) studied the use of DEA in effectively measuring the efficiency of bridge replacements and rehabilitation programs of state highway agencies. Zhang et al. (2015) also explored the ability to evaluate technical efficiency change and technological change of these operations using DEA. Technical efficiency change and technological change were evaluated using the Malmquist productivity index (MPI) model. MPI, also known as total factor productivity change, was developed as a combination efficiency and productivity to be an appropriate tool in measuring the change in productivity of DMUs over time (Cook & Seiford, 2009; Zhang et al., 2015). To perform the analysis, Zhang et al. (2015) used a modified input-oriented variable returns-to-scale model with 48 total DMUs (state DOTs), six inputs, and two outputs. Jalili (2015), used DEA as a means to evaluate performance of the Wyoming Highway Patrol divisions and provide benchmarks. Jalili (2015) used an output-oriented BCC model with both controllable and uncontrollable inputs to perform the assessment. Marchetti and Wanke (2016) also used DEA as a means to assess efficiency in the transportation sector. In their research, Marchetti and Wanke (2016) looked at the application of DEA to determine efficiencies in Brazil's freight transportation by rail. Their study used a combination of two output-oriented DEA models (one CCR model and one BCC model) with two inputs, one output and 60 DMUs.

The abovementioned instances pertain to the use of DEA relating the transportation industry; however, DEA has been used across countless industries and sectors across the world. Carnes et al. (1998) provided a DEA methodology to evaluate and benchmark building energy consumption in service institutions in terms of productivity. McCabe et al. (2005) researched the application of DEA in the construction industry to provide a benchmarking tool for owners to standardize contractor prequalification. Trappey and Chiang (2008) used DEA as a benchmarking technique for planning in new product development. Abdullah et al. (2012) evaluated the efficiency of internal company projects using DEA. Shirouyehzad et al. (2012) used a DEA approach for measuring employee efficiency in terms of physical working conditions and organizational commitment. Monika and Mariana (2015) explored the use of DEA in human resource controlling as a qualitative human resource indicator. And, Visani et al. (2016) investigated the use of DEA as a new approach to total cost of ownership. These examples are not meant to encompass all the potential uses of DEA but are intended to show the vastness of potential uses as well as provide further historical uses of DEA outside of the transportation industry. Table 1 summarizes the aforementioned 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

2.3 - Efficiency and Productivity in Shipyards, Maintenance, and Facilities Management

The previous section of this literature review discussed various historical and current applications of DEA. The succeeding section is focused on performance evaluation methods used to evaluate performance in shipyards, maintenance, facilities management, and other similar applications. Along with DEA methodologies, other tactics and approaches to performance evaluation are also discussed. Discussion is provided for each application that includes the methodology and variables used, the area of application, the purpose of the evaluation, as well as discussion of the results of the evaluation.

2.3.1 - Approaches to Evaluate Efficiency and Productivity in Service Related Industries

The notion to study efficiency and productivity in areas relating to shipyards, maintenance, and facilities management has been around for quite some time. Traditional tactics of performance measurement and benchmarking relating to these fields has been researched in multiple studies (International, 2016, 2017; F. Lamartin & Powell, 1980). Along with traditional approaches, various other studies others have proposed methods utilizing DEA (Charnes et al., 1984; Itoh, 2002; Macmillan, 1987; Park, Lee, & Zhu, 2014; Pires & Lamb, 2008; Rabar, 2015; Tongzon, 2001; Wong, Leung, & Gilleard, 2013). Of these studies, only the studies of Chudasama (2010), Lamartin (1980), Guofu et al. (2017) International (2016,2017), Ok and Feng (2017), Park et al. (2014), Pires and Lamb (2008), and Rabar (2015) are directly concerned with productivity and benchmarking in shipyard maintenance or shipbuilding activities. The remaining studies are either connected to maintenance, shipyards, or facilities management (FM) in general.

A new method for manpower decisions in shipyards, utilized in the 1980's by a large military shipyard operation, included a "profiling" approach (Lamartin, 1980). The approach included considerations of multiple variables, which contribute to the overall productivity. It was recognized during that time that measuring ship repair and overhaul productivity is much more difficult than measuring shipbuilding productivity – often because the goal in shipbuilding was to estimate construction costs (Lamartin, 1980). The variables used during this particular study included relationships between productivity, work force characteristics, and working conditions. This method, like many efforts concerning efficiency, often serves the mission to review individual or group productivity levels using a single input/single output method. Under Lamartin's "profiling" approach, productivity was measured using standard input to output ratio. To measure overall productivity, Lamartin (1980) suggested carrying out a three step measurement process of setting baselines, observing variations from baselines, and combining individual productivity measurements to develop overall efficiency. While this method does provide productivity measurement, it is limited to single input/single output situation and requires common measurement units to combine individual measurements into an overall measure of productivity making the results subjective.

Charnes et al. (1984) studied the use of DEA in measuring the efficiency of maintenance units in the United States Air Force. In this study, Charnes et al. (1984) identified four basic areas of concern evaluating the efficiency of maintenance units. These questions concern the highest level of service achievable, shortfalls, effective resource acquisitions, and management system improvements. Data collected for inputs and outputs was taken from fourteen separate Air Force maintenance wings. The methodology used for analysis was the basic CCR model with eight inputs and four outputs. Results of the study determined the inefficient maintenance units and provided a basis for improvement. While this study concerns maintenance, its methodologies do not provide a basis for which shipyard manpower levels can be determined.

Tongzon (2001) and Itoh (2002) both conducted studies relating to shipyards however, both studies focused on the efficiencies of port operations as a whole. Tongzon's (2001) study was concerned with twelve international ports and used six inputs and two outputs. Itoh's (2002) study only included eight major container ports in Japan. Itoh's study took advantage of both the CCR and BCC models to analyze the efficiency of Japanese ports using three inputs and one output. Wong et al. (2013) researched the use of DEA in facilities management to overcome benchmarking challenges. Four inputs along with nine outputs were used in the evaluation of nine buildings.

First Marine International (FMI) completed a two-part study (project 9Y1755) for the US Naval Shipbuilding and Repair Industry to find strategies for performance improvement (International, 2016, 2017). They researched performance targets expressed in terms of the budget required to carry out a specific task. In this case, the research simply utilized a survey to compare categorized tasks, technologies and skills to assess and improve shipyard productivity. Eight shipyards participated in the survey, five large and three mid-tier. Target ranges were reported and the benchmarks are referenced with each update of the report to identify possible improvements from year to year (International, 2016). Key facility and equipment recommendations provided by FMI to be included in each shipyards' benchmarking report are materials handling and storage, unit and block assembly, welding, module building, support and services, workstation organization, pipe shop, and construction points. From the second part of the report, it was determined that the top five industry performance improvement areas are: approach to performance improvement; organization and approach to work; support for work; planning scheduling and control; and commercial relationships (International, 2017). Although this type of report is beneficial, the information is reported in aggregate and not very specific for the needs to outline manpower roles in the shipyard industry.

Pires and Lamb (2008) proposed an approach for establishing performance targets for shipbuilding operations using Data Envelopment Analysis (DEA). The expected outcome of the research was to make it feasible to estimate productivity and project duration, while accounting for the many various external components that influence shipyard performance. Namely, these external components that influence shipyard productivity and project duration include the shipyard's output patterns, the technological levels of the shipyard, and the industrial environment of the region where the shipyard is located. Pires and Lamb (2008) concluded that in order to become competitive with the international standards the technological levels of many Brazilian shipyards must be dramatically updated, and shipyards must be greatly modernized. This suggests that the level of technology for a shipyard is directly related to the productivity/performance of that shipyard. Consequently, the technology levels of shipyards must be considered when comparing the performance of one shipyard to another. To account for technology levels for each shipyard, Pires and Lamb (2008) used a synthetic comparative index they called a technological development index (ITECH) as an input to the DEA evaluation. The index was compromised of four activity groups which are graded from 1-5, with a grade of five (5) being state of the art. The activity groups used to determine technology level included fabrication and assembly, erection and outfitting, product and process engineering, and organization and management activities. Each activity group was graded for all shipyards, and the input variable ITECH was calculated by taking the average of the mean values for the groups of activities. Along with technology level, Pires and Lamb (2008) also included shipyard capacity and quality of industrial environment as production influencers in their DEA evaluation shipbuilding facilities.

Chudasama (2010) evaluated the efficiency of shipbuilding in Indian shipyards using an input-oriented DEA model to assess the extent of optimal resource allocation to achieve the shipyard's planned targets. Efficiency is capable of being measured in this context because the basis behind efficiency in DEA is the ability to convert inputs to outputs. The model used by Chudasama (2010) was input-oriented, meaning that the efficiency scores produced by the model represent the smallest proportion of the existing inputs a shipyard can use and still produce its existing output if it was using the best practices observed throughout the DMU sample. The orientation of the model was chosen based on the assumption that the main objective of a shipyard is to optimize the allocation of resources or to minimize the inputs required to reach a targeted level of output. Chudasama (2010) evaluated the efficiency of the shipyards based on three input variables and one output variable determined through discussion with industry experts. Like similar studies, shipyard facility characteristics and capabilities were utilized as input variables for the DEA model. The input variables used for this model include shipyard capacity in deadweight tonnage, maximum length of vessel built, and total number of employees. The lone output variable for the model was annual income for the shipyard. The results of the study were evaluated, and sources of inefficiency were analyzed based on input slacks, peer group, and peer weights. The analysis of inefficiencies allowed Chudasama (2010) to benchmark performance targets and provide suggestions to make the operations of underperforming shipyards more efficient.

Park et al. (2014) proposed an approach for the performance evaluation for the Block Manufacturing process in a Korean shipbuilding company. The methodologies used for the evaluation include process mining along with DEA. Performance measurements used by Park et al. (2014) were number of unit operations, waiting time, total execution time, material amount, and gap between planned and actual working time. From these performance measurements, Park et al. (2014) created two inputs (total execution time and waiting time) and two outputs (number of operations and material amount). Data for the performance analysis was obtained from databases of actual data supplied by production information systems. Results of the analysis provided guidelines for improvement of underperforming units in relation to the entire manufacturing process. This approach set forth by Park et al. (2014) provides great insight into productivity evaluation of ship manufacturing; it does not provide the necessary information for the study of manpower efficiency and productivity in a ship maintenance setting.

Rabar (2015) used DEA as a means of setting key performance targets for shipbuilding in five Croatian shipyards. Best practice shipyards were identified from the efficient frontier developed by the DEA model and used as benchmarks of performance. Five variables were used during the analysis, three input variables and two output variables. The input variables selected were number of employees, number of effective working hours, and total expenditures. The output variables included total delivered compensated gross tonnage and total revenue. Since the number of DMUs was relatively small, Rabar (2015) used window analysis to evaluate each shipyard on a yearly basis. Using window analysis creates more DMUs because it treats each time period as a separate DMU. For example, if there were four DMUs and the available data was from 2015 to 2017, the total number of DMUs for the model would increase from four to twelve using window analysis because each period is treated as a separate DMU. For the analysis, Rabar (2015) used both the CCR and BCC models in an output orientation. Each model was ran with both a CRS and VRS due to the uncertainty concerning the appropriate RTS to use in the case of shipyard performance. Inefficiencies were evaluated based off technical efficiency and scale efficiency of the DMUs.

Guofu et al. (2017) developed a model for the measurement and evaluation of shipbuilding production efficiency which used DEA as an evaluation tool. The efficiency model utilized four different DEA models, both an input and output oriented CCR as well as a BCC model in both orientations. Guofu et al. (2017) also included a four-step conceptual framework for selecting the appropriate data, methodology, performance indicators, and production variables for evaluation of shipbuilding efficiency. The conceptual framework was designed based off the theory that production efficiency in shipbuilding is the combined effect of multiple factors related to production (Guofu et al., 2017). Therefore, to effectively evaluate shipbuilding production efficiency, the efficiency evaluation model must be inclusive of all factors which affect production. Guofu et al. (2017) used their efficiency model to evaluate shipbuilding production efficiency of 13 Chinese shipbuilding facilities. The model included two outputs, number of vessels delivered and delivered compensated gross tonnage (cgt) along with four production inputs, number of docks, total area of docks, number of cranes, and maximum lifting capacity. To evaluate the results of the model, several production efficiency indicators were defined at the firm, organization, activity, and product level. These indicators were used to evaluate each shipbuilding facility and allowed the sources of inefficiencies to be better identified and related to a specific element of shipbuilding production. Guofu et al. (2017) used the results of this evaluation to provide valuable information to each shipbuilding facility concerning the direct causes of each inefficiency as well as strategies and suggestions for further improvement.

Ok and Feng (2017) applied a DEA model in efforts to analyze the efficiency of the Chinese ship repair industry. The analysis evaluated 12 ship repair facilities including both public and private companies. Also included in the work of Ok and Feng (2017), is an extensive literature review of similar studies along with a table summarizing each of the referenced studies. An input-oriented CCR model encompassing four inputs and three outputs was used during the evaluation. The input variables chosen were total dock length, total dock area, total docking capacity in tons, and number of production employees. The output variables utilized were total annual revenue, number of repaired ships, and the service range of the repair facility. Ok and Feng (2017) used the results of the analysis to analyze any inefficiencies, to determine the strengths and weaknesses of each facility, and to provide productivity improvement measures for the inefficient repair facilities. The sources of inefficiencies were analyzed by finding the causes through the development of an efficient DMU based off a reference group of efficient DMUs. To provide accurate and appropriate efficiency improvement measures to each inefficient repair facility, Ok and Feng (2017) separated public and private companies during evaluation of the results. Results of the analysis show that, of the selected facilities, the private facilities were more efficient than public facilities. Ok and Feng (2017) suggest that public facilities are inefficient when compared to private companies because of increased liabilities and financial risks, and their systematic setup makes them less flexible to changes. Regardless of company type, the authors suggest that the most important factors for improvements in ship repair efficiency are continuous improvement and upgrades to the facility, technology, and industry while ensuring the management style is ever evolving and not becoming stagnant.

According to Bröchner (2017), many studies have been done concerning workplace productivity but there has been very little research on the direct productivity of facilities management. This identified gap in research is similar for the shipyard industry and the lack of DEA efficiency evaluations of maintenance and repair. Providing an objective means for decision-making in terms of manpower is fundamental for increased productivity and performance. Regardless of the fact that the aforementioned studies relate to efficiency and productivity evaluation of shipyard maintenance in some way, none of these studies provide an exact methodology for the study on manpower and efficiency of the Manns Harbor Shipyard. However, these prior studies do provide background knowledge pertaining to the types of data to be used, quantities of inputs and outputs, along with potential methodologies. A visual summary of these previously used methods can be seen in Table 2.

Table 2: Previous Methods of Performance Measurement in Shipyards/Maintenance/FM

Author	Method	Application Area	Description
Lamartin (1980)	Profiling (single input/output)	Shipyards	An approach to manpower decisions in shipyards based off of productivity
Charnes et al. (1984)	DEA	Airforce Maintenance	Application of DEA to determine efficient units in Airforce maintenance
Tongzon (2001)	DEA	Shipyards	Study of the efficiencies of port operations
Itoh (2002)	DEA	Shipyards	Study of the efficiencies of port operations
Pires & Lamb (2008)	DEA	Shipbuilding	Analysis of Brazilian shipyards using DEA to establish performance targets
Chudasama (2010)	DEA	Shipbuilding	Efficiency evaluation of Indian shipyards using DEA
Wong et al. (2013)	DEA	Facilities Management	Application of DEA to overcome benchmarking challenges in facilities management
Park et al. (2014)	DEA	Shipbuilding	DEA performance evaluation of the Block Manufacturing in a Korean shipbuilding company
Rabar (2015)	DEA	Shipbuilding	Application of DEA to evaluate the performance of Croatian shipyards and set key performance targets
International (2016,2017)	Survey/Report	Shipbuilding/repair	Two-part study of US Naval Shipbuilding and Repair Industry for performance improvement
Guofu et al. (2017)	DEA	Shipbuilding	DEA application to evaluate the efficiency of shipbuilding production in Chinese shipyards
Ok & Feng (2017)	DEA	Ship Repair	Application of DEA to evaluate the performance of the Chinese ship repair industry

CHAPTER 3: RESEARCH METHODOLOGY

To evaluate the efficiency of Manns Harbor Shipyard, the research team conducted visits and held interviews with industry experts from other ship repair facilities that are similar in terms of their operations. Due to the limited number of shipyards and competitiveness of the industry, the majority of shipyards contacted were unwilling to participate or provide detailed operational data to the researchers. In spite of these challenges, three shipyards agreed to participate in this study fully while an additional shipyard agreed to conduct a visit but disinclined to offer any operational data. Due to the nature of this research and confidentiality agreements with the participating entities, the names of shipyards will remain anonymous and information in this report will be conveyed in aggregate. Of the participating shipyards, all of which are private entities, two are located along the Gulf Coast while the remaining two shipyards are located on the Atlantic Coast. To classify these participating shipyards, this research utilizes 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 general measure of productivity is too generic to assess overall operational efficiencies. Shipyard operations, especially when considering the differences between public and private entities, can vary greatly and therefore the difficulty with any single-factor productivity measures is that it is easy to obtain a false sense of increased productivity due to a factor that provides no company value. For example, many operations focus on the basic labor related factors such as a total time for a task, for a single trade's output. However, efficiency can be improved through planning and increased use of the combined time for all trades that produce an output for a product. Improving the efficiency of one trade without consideration of project scheduling will negate the overall mission. Therefore, the research aimed to take a multifactor perspective through both qualitative and quantitative review of shipyard operations. The methodology used to carry out this research consists of the four basic steps listed below. The succeeding subsections will provide detailed descriptions and discussion of each research step.

- Step 1 – Data collection through shipyard visits and interviews
- Step 2 – Qualitative assessment of shipyard operations
- Step 3 – Quantitative assessment of shipyard operations using DEA
- Step 4 – Analyze assessment results and provide recommendations

3.1 - Maintenance and Repair Facilities Overview

The most appropriate description of the shipyards similar in operation to Manns Harbor 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. The participating shipyards included three facilities in the "Major Shipyard" classification along with one facility classified as a "Medium and Small Shipyard".

During visits and interviews with experts at each shipyard, questions were asked concerning manpower levels and types, maintenance activities, facility characteristics, organizational structure, management styles and strategies, and typical day-to-day operations. Data gathered from these interviews, was used to evaluate the similarities and differences of shipyards and their operations. The evaluation of data and thorough investigation of shipyard operations also allowed for a list of production parameters to be established for vessel repair and maintenance. A summary of general characteristics concerning each shipyard can be seen in Table 3 below. Due to the aforementioned constraints, the name for each shipyard will be kept confidential. Manns Harbor Shipyard will be referred to as Shipyard A or SY_A and the other shipyards will be referred to in similar fashion.

Table 3: Shipyard General Characteristics

	Shipyard Classification	**Org. Type**	**M&R Labor**	**Full-Time Employees**	**Org. Structure**	**Max. Drydock Capability**	**Apprentice Program**
Manns Harbor (SY_A)	Medium/Small	Public	In-house only	65	See Fig. 2a	867 tons, 220' LOA x 50' Wide	No
Shipyard B (SY_B)	Major	Private	In-house and subcontracted	250	See Fig. 2b	8,100 tons, 341' LOA x 110' Wide	No
Shipyard C (SY_C)	Medium/Small	Private	In-house and subcontracted	25	See Fig. 2c	480 tons, 200' LOA x 38' Wide	No
Shipyard D (SY_D)	Major	Private	In-house and subcontracted	380	See Fig. 2d	89,600 tons, 751' LOA x 110' Wide	Yes
Shipyard E (SY_E)	Major	Private	In-house and subcontracted	Undisclosed	See Fig. 2e	17,640 tons, 620' LOA x 88' Wide	Yes

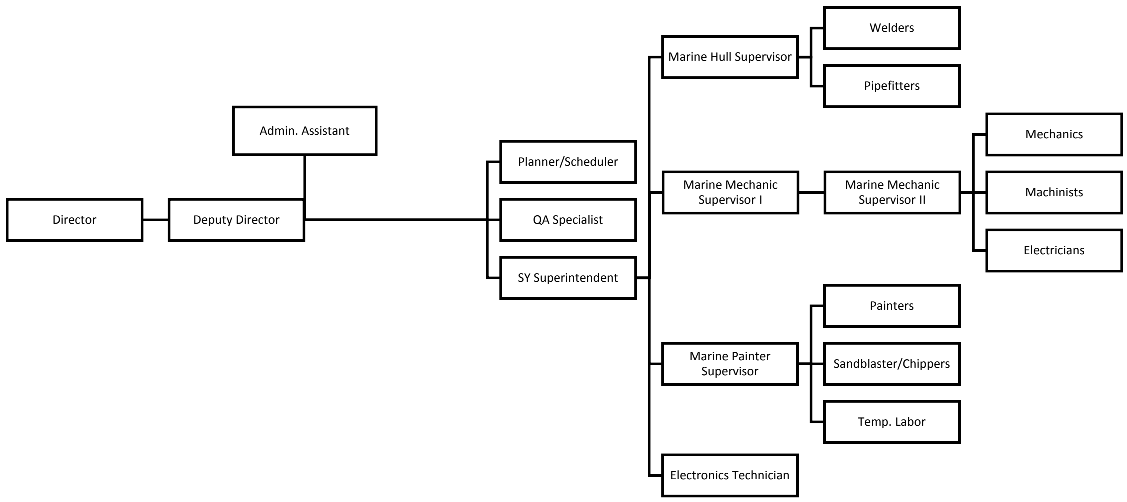

Figure 2a: SY_A Organizational Structure

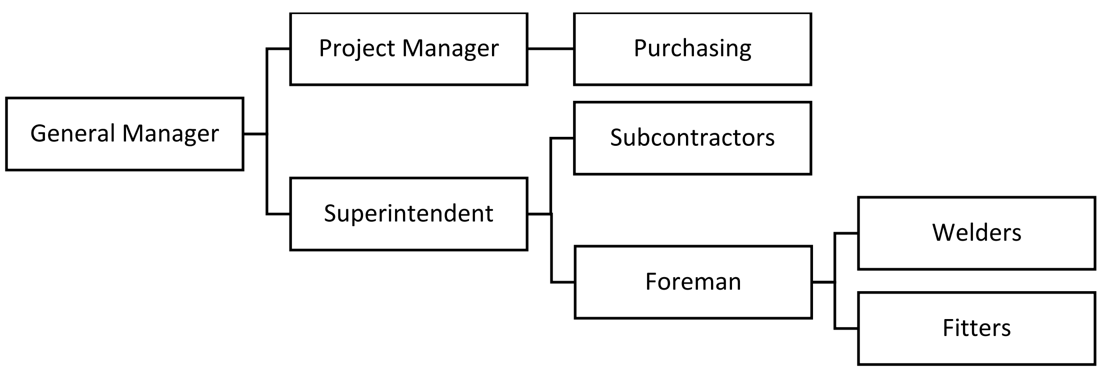

Figure 2b: SY_B Organizational Structure

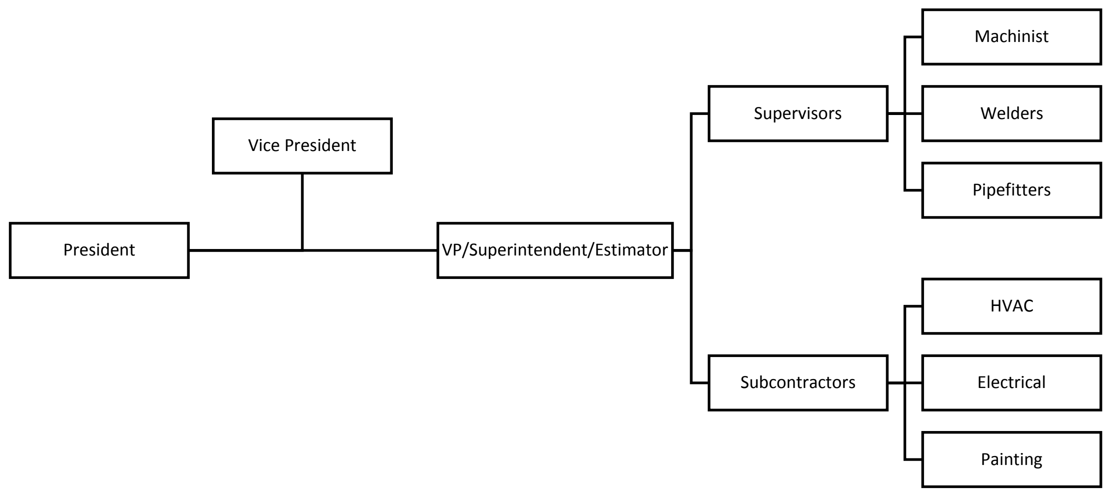

Figure 2c: SY_C Organizational Structure

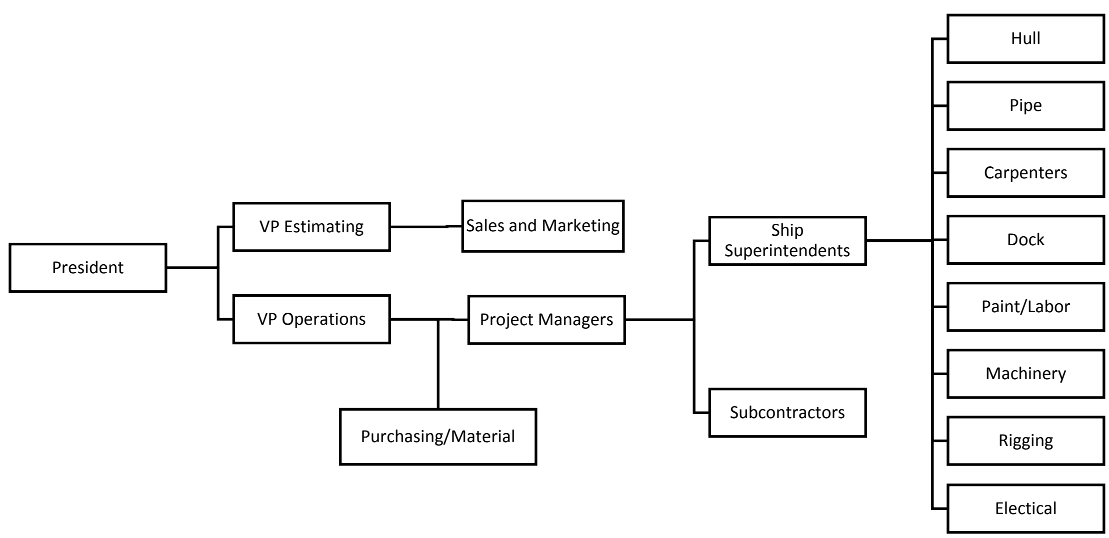

Figure 2d: SY_D Organizational Structure

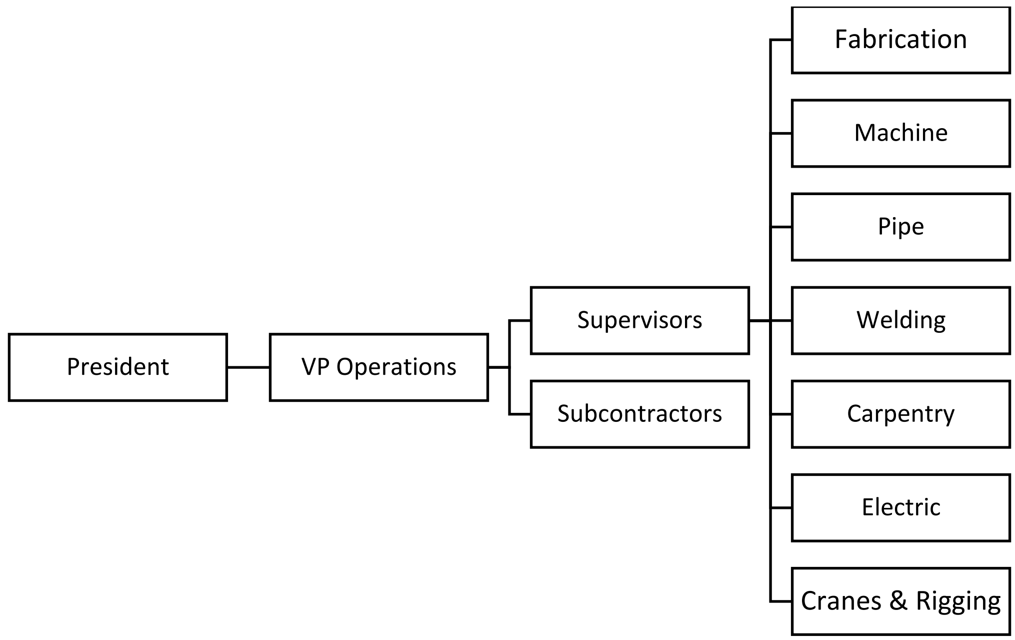

Figure 2e: SY_E Organizational Structure

Through discussion and investigation of each shipyard, it was identified that the trades employed by each facility and the maintenance activities carried out during their operations remained analogous from shipyard to shipyard. However, manpower levels, types of labor, organizational structure, technologies, facility capabilities, and management strategies vary from one operation to the next. These variations are mainly due to the organization type (public or private), facility size, and types/size of work done at each facility. As previously stated, with the exception of Manns Harbor (Shipyard A), all shipyards participating in this study are private businesses. This is to the very limited number of public shipyards in the United States that remain operational. The researchers were unable to locate any similar-sized public shipyards. Excluding Manns Harbor (Shipyard A), there are only five active public shipyards across the entire country (Stegall, 2017). Conversely, the active public shipyards are larger facilities and perform the majority of their work on military vessels and other larger ships. Because of this, the operations of these public shipyards are not comparable to the operations of Manns Harbor (Shipyard A). Moreover, Manns Harbor (Shipyard A) is the only facility in which subcontracted labor is not utilized. All of the remaining shipyards utilize varying levels of subcontract and in-house labor for their maintenance and repair operations. Despite slight variations amongst the shipyards under evaluation, all of the facilities complete similar types of work on corresponding types of vessels, using comparable types of technologies and personnel. Because of these parallels among shipyards, the homogeneity requirement of DMUs used for DEA evaluation is satisfied.

Similar to Manns Harbor (Shipyard A), interviews with management personnel from other facilities indicated that increased labor requirements and reduced employee retention are the primary issues with regards to downtime and operational efficiency. A representative from Shipyard E stated that painting is an area of continuous frustration and at any given time, the shipyard employees up to 100 additional temporary workers to meet the required manpower staffing levels. While this is just one example, the remaining shipyards employ similar tactics such as temporary employment and subcontract labor to accommodate for the lack of manpower. Alternatively, because the lack of manpower can be primarily attributed to a lack of training and poor retention, two of the participating shipyards, Shipyard D and Shipyard E, have established apprenticeship programs with local technical colleges. An apprenticeship is a combination of on-the-job training (OJT) and related classroom instruction under the supervision of a journey-level craft person or trade professional in which workers learn the practical and theoretical aspects of a highly skilled occupation (WSLND, 2017). As a part of these apprenticeship programs, each apprentice is employed full time by the shipyard and compensated competitively throughout the duration of the required classroom instruction and training to advance to journeyman level for their particular trade. These apprenticeship programs not only provide adequate and relevant training, they also help with employee retention in the shipyards that have established them because employees understand and recognize the potential for advancement inside the organization.

Outside of the aforementioned apprenticeship programs, several additional strategies have also been employed by shipyards to increase productivity and efficiency or alternatively, to decrease downtime and schedule overruns for their projects. One tactic observed in several of the shipyards under investigation, was to dedicate specific personnel as project managers for each project undertaken. A representative from Shipyard D stated that project management for their organization is key to connecting the schedule and efficiencies with the needs of the organization. The employment of project management positions allow for the workload of the superintendent and supervisors to be reduced. Instead of dedicating their time to planning, estimating and scheduling, the introduction of a project management role allows for the superintendent and supervisors to better manage their workforce and utilize their time in the field, rather than an office. Furthermore, the addition of the project management role allows for management and tradesmen to work together to maintain the project schedule, creates an additional means of checks and balances within the organization, and most importantly allows the employees to dedicate their time to their area of expertise. Other strategies implemented include bonuses and incentives for on time or early project completion as well as changes to management strategy or style. For example, Shipyard B has implemented lean operation and direct communication strategies to improve efficiency. Alternatively, Shipyard D has implemented an on time-focused management strategy to improve the operational efficiencies of the shipyard. Additional strategies to improve efficiency deal with improvements and upgrades to shipyard facilities and equipment technology, as well as the use of computerized maintenance management systems (CMMS) specifically designed for marine maintenance and repair operations.

While this section discusses the similarities and differences between the shipyards under evaluation, it is only meant to establish qualitative factors in which efficiency can be influenced. Despite the application of various strategies aimed at increasing operational efficiency, these strategies were implemented on a case-to-case basis and cannot be applied in every circumstance due to a multitude of factors concerning the organization and its makeup. However, evaluation of these shipyards allowed for a set of production parameters, discussed in a later section of this report, to be established for use as variables in the DEA model. Additionally, establishment of these qualitative factors will assist the researchers with providing suggestions and recommendations to the NCDOT concerning potential tactics to increase the productivity and efficiency of the Manns Harbor operation.

3.2 - Facility Summaries Qualitative Review

3.2.1 - Manns Harbor – Shipyard A

Manns Harbor Shipyard is one of the six active public shipyards in the Unites States and is the only public shipyard that maintains a fleet of ferries. The other public shipyards conduct the majority of their work on military vessels and other large supply vessels. In addition to the ferry fleet, Manns Harbor is used to dock and repair all tugs, workboats and dredges operated by the NCFS. The shipyard utilizes a marine railway for all dry-docking and launching operations. The facility has the capability to dry dock up to three vessels at one time. The largest vessel in the fleet that must be dry docked by the facility is 220 feet in length, 50 feet in width and weighs 867 gross tons. Manns Harbor utilizes forklifts and cranes for material lifting and transportation. The shipyard is also inclusive of a 10-story enclosed paint facility and an indoor machine shop outfitted with both mills and lathes.

Manns Harbor utilizes in-house labor to complete all of their maintenance work without any subcontracted labor. The shipyard employs approximately 65 full-time employees along with temporary laborers from time to time as deemed necessary. Despite having 65 full-time employees, the Shipyard Superintendent stated that only 44 are production employees. The trades employed by the shipyard include machinists, painters, chippers, electricians, welders, pipe fitters, and mechanics. Of these trades, the Shipyard Superintendent stated that welders are the hardest to retain and have the highest turnover of any trade in the shipyard. The paint department, which is inclusive of painters as well as chippers, provides the majority of the labor hours for the Manns Harbor operation. One major difference between Manns Harbor and the other shipyards included in this study is that it is a state-owned public shipyard, while all of the others are private. Being a government entity, the shipyard is required to observe all federal holidays and must follow the state's work calendar. Manns Harbor operates Monday through Friday from 7:30 am to 3:30 pm. The workday schedule includes a morning break, a lunch break, and an afternoon break.

As seen in the organizational structure shown above in Figure 2a, the shipyard does employ a shipyard planner/scheduler. However, until recently this position has been vacant. Because of this, the shipyard does not have any formal planning, estimating, or scheduling procedures. Moreover, despite the addition of a planner/scheduler, there is no direct link between the planner and the field personnel. All information must first be communicated to the Shipyard Superintendent, then to the department supervisors before it reaches the tradesmen in the field. As a result, the Shipyard Superintendent is responsible for maintaining and tracking progress for each repair project and is the direct line of communication between repair operations and the management team. Project estimation is done prior to the arrival of each vessel during a production meeting between the supervisors, the shipyard superintendent, and management team through expertise and evaluation of the vessel condition. Estimates are based on the man-hours required in each department rather than a quantity of work to be done (i.e. square feet of painting) and are completed using Excel spreadsheets. These estimates are used as the schedule to track the progress of the project.

During a visit to the shipyard, when asked about incentives and employee advancement, the Shipyard Superintendent stated that there are very little to no incentives offered to the employees and that there is no way to advance once hired. Moreover, he stated that once hired employees would make the same salary with no increase or raise unless the entire NCDOT increases pay. The Shipyard Superintendent partially attributes this to the high rate of turnover inside of the shipyard. He stated that the majority of the time, when welders or other skilled trades leave it is related to a lack of incentives and no chance of advancement throughout the organization.

Manns Harbor Shipyard utilizes the NCDOT SAP computer software to track and record man-hours on each maintenance and repair project. However, the NCDOT-Ferry Division has only utilized this system for approximately 18 months. Therefore, the amount of computerized historical data available for reference is very limited. Furthermore, through discussion with the Shipyard Superintendent, it was stated that despite having a computerized management system the system is utilized by the entire NCDOT and is not setup specifically for ship maintenance and repair. As a result, the software is not as useful and intuitive for the shipyard operations compared to highway maintenance or bridge projects, making the use of the software as a maintenance management tool difficult for ship repair projects.

3.2.2 - Shipyard B

Shipyard B has three dry docks, five areas where work can take place “dockside”, and four new construction areas. The shipyard lies on a 50-acre site with one mile of waterfront property and a 30,000 square feet enclosed fabrication facility with two ten-ton overhead gantry cranes. Dock 1, the largest of the dry docks at Shipyard B, has a maximum lifting capacity of 8,100 tons, a wing wall depth of 20 feet and can accommodate vessels up to 341 feet in length and 110 feet in breadth. Dock 2 has a wing wall depth of 25 feet, a lifting capacity of 5,000 tons and can accommodate vessels up to a maximum of 292 feet in length and 82 feet in width. The smallest dry dock at this shipyard, Dock 3, is used mainly for barge repair. Dock 3 has a lifting capacity of 2,200 tons, a length of 208 feet, a width of 61 feet, and a wing wall depth of 20 feet. Additionally, Shipyard B maintains a variety of crawler cranes, up to 230-ton single lift capacity, as well as a wide range of smaller mobile cranes in order to handle demanding lift requirements.

Shipyard B’s operation utilizes a lean organizational structure illustrated in Figure 2b above. During the visit to Shipyard B, the Project Manager/Estimator stated that project management for their organization is key to connecting the schedule and efficiencies with the needs of the organization. Additionally, the representative stated that there are times when the project manager may have direct contact with the Foreman. The majority of these instances of direct contact are associated with schedule issues. The Project Manager indicated that a majority of his time is spent in the field rather than in an office. At Shipyard B, the Project Manager is responsible for planning, estimating and scheduling and operates directly with the Superintendent and the Foreman to maintain the schedule.

Shipyard B's manpower utilizes 25 to 30 percent in-house personnel with the remaining manpower provided through subcontracted work. Shipyard B's manpower strategy for multiple vessels in the yard is to develop work crews for each vessel. For example, if there are five boats in the yard, there are five crews. Each crew stays on the assigned vessel from project start to finish. This strategy is achievable because the employees understand their job role includes multiple-task duties. There are approximately 250 employees at Shipyard B. The workforce is inclusive of a diverse ethnic employee makeup. In addition, there are opportunities for many of the employees to advance through promotions inside the company. Shipyard B operates seven days per week with most employees working a 6-day schedule. The company has an established recognition program with monthly leadership and quarterly awards for employees who exemplify good safety and work efficiencies. This is in the form of both a basic "recognition" as well as monetary rewards. The delineation of trades with regard to in-house work and subcontracted work are as follows:

- In-house:
  - Machining
  - Painting
  - Fitting and Welding
- Subcontracted:
  - Carpentry
  - Electrical
  - Gas-freeing Process

In addition to the mobile and crawler cranes mentioned previously, Shipyard B utilizes advanced management technologies and equipment in their repair operations. In terms of increased efficiency and productivity, the shipyard utilizes a robotic paint-blasting slurry method for hull preparation and paint removal rather than the time consuming manual method, that utilizes hand sanders. A shipyard representative stated that when compared with the manual method, the slurry method is quicker, more efficient, and removes any environmental regulation responsibility from the shipyard because the waste from the process is collected and disposed of by an outside vendor. Additionally, the management team at Shipyard B employs a "home-grown" Computerized Maintenance Management System (CMMS) that has been developed over the past ten years for. The CMMS uses an Oracle-based Integrated Work Management System (IWMS) to complete estimates. Moreover, the IWMS allows management to track costs and schedule throughout each project by producing progress reports. These reports have built-in "efficiency-ratios" to assist the Project Manager with tracking progress. Additionally, the IWMS allows any changes or updates to the scope of work to be directly loaded in to Microsoft Project, which enables the project schedule to reflect these changes without any additional work. Currently, Shipyard B only utilizes the IWMS for new ship construction and repair projects are tracked in a similar fashion to the system via Excel spreadsheets. However, the shipyard is in the process of planning the integration of repair work into the IWMS system so that all projects are estimated, tracked, and updated through a single means.

In addition to the advanced technologies, Shipyard B has also implemented strategies processes aimed at improving organizational and operational efficiencies. The first of the strategies is reflected in the organizational structure of the shipyard. The introduction of the Project Manager role along with the implementation of lean operation and direct communication strategies is the primary means of tracking and improving internal efficiencies. These strategies ensure that initial planning is done accurately and that there is a direct line of communication from management to field personnel so that the project schedule is maintained and the vessel is delivered on time. Another efficiency strategy implemented is a strategy Shipyard B calls "rolling back". This strategy requires the work crews to clean the shipyard and take all tools, hoses and equipment back to inventorying at least once per week. This keeps the yard clean, supports with safety procedures, and assists with inventory of tools. Another strategy implemented to improve efficiency is to maintain workday schedule that does not include any breaks except a 30-minute lunch break. It is understood in the shipyard that if an employee requires a break to use the restroom or get water that they take it and return to work as soon as possible. The final efficiency strategy implemented by Shipyard B deals with the sequence of repair activities. As an alternate to the sequence of work at most repair facilities, Shipyard B begins their repair operation with an overall paint job once slurry-blasting activities are completed. This assists to mitigate the amount of rework for painting areas that begin to rush after blasting and sets a stage for a clean initial work area.

3.2.3 - Shipyard C

Shipyard C is a full service repair, conversion, and new construction shipyard that encompasses 46 acres of property. The shipyard has approximately 2,000 feet of waterfront property, which is inclusive of three boat slips for repairs that do not require dry-docking. The facility operates a 480-ton lifting capacity marine travelift capable of handling vessels up to 38 feet in width for all dry dock repairs and new vessel construction. In addition to vessel repair and construction, Shipyard C also provides dry storage for vessels up to 200 feet in length. Shipyard C has constructed over 500 vessels, many of which were ferries. Furthermore, Shipyard C has constructed four ferries currently in operation for the NCFS.

Shipyard C's current employee level is approximately 25 in-house employees, 20 of which are specifically shipyard production employees. The majority of the work completed using in-house labor is steel and hull work. Therefore, the trades employed by Shipyard C include machinists, pipefitters, and welders. The repair services provided directly by Shipyard C are USCG inspections, underwater inspections, blasting and painting, audio gaging, and steel replacement. In addition to the in-house trades, Shipyard C maintains a team of subcontractors for other ship repair needs including electrical, HVAC, carpentry, machine work, and propeller work.

Shipyard C completes their estimates for repair using spreadsheets and tracks employee and subcontracted labor hour using Intuit QuickBooks. As seen in Figure 2c above, the Estimator/Superintendent is responsible for creating estimates for each project as well as tracking and monitoring progress to ensure the project schedule is maintained. At Shipyard C, no formal schedule is developed for each project; instead, the estimate serves as the schedule for the project. However, despite no formal planning or scheduling Shipyard C reports high levels of performance and on-schedule project completion.

3.2.4 - Shipyard D

Shipyard D operates on a retired naval shipyard, which is leased through a naval shipyard redevelopment organization. Shipyard D has four dry docks and seven full service piers inclusive of over 8,000 feet of deep-water pier space. The largest of the dry docks at this operation is capable of handling vessels up to 90,000 tons, 751 feet in length, and 110 feet in width. The largest of the seven full service piers can handle vessels up to 1,000 feet in length. In addition to the dry docks and piers, Shipyard D is inclusive of 2,500,000 square feet of indoor manufacturing and warehouse space. The indoor space is inclusive of machine, welding, pipe, and electrical shops. Additionally, Shipyard D operates eight 60-ton capacity gantry cranes on a continuous rail system along with four tower cranes for any lifting needs. During the visit to the shipyard, a representative from the shipyard stated that the operation typically repairs up to 60 vessels annually that range in size from 200 feet to 1000 feet in length. Shipyard D performs repairs on various types of vessels including tugs, barges, cargo ships, research vessels, offshore support vessels, military and government vessels, as well as ferries.

Shipyard D has approximately 380 full time employees along with 30 service companies that perform subcontract work on their projects. In total, Shipyard D's overall workforce including subcontractors is approximately 1,100 employees. Because of the immense size of the operation and extensive indoor space, many of the buildings on-site are subleased to subcontractors and vendors who perform work and provide services on many of Shipyard D's repair projects. The on-site shops and departments at Shipyard D include purchasing and materials, hull, pipe, carpentry, docking, paint and labor, machinists, rigging, and electrical. Moreover, due to the vast amount of resources available at the shipyard, the sequence of work is much different from that of a typical ferry maintenance operation and typically involves multiple departments and subcontracted vendors completing work simultaneously to reduce repair time. As shown in Figure 2d along with the various skilled trades, Shipyard D also employs a management team that includes shipyard superintendents, project managers, marketing and sales professionals, a vice president of estimation, a vice president of operations, as well as various administrative and executive employees. For all repair projects, an estimate is completed by the vice president of estimation using Excel spreadsheets. The estimate is inclusive of internal cost codes for each activity, as well as an hourly unit cost for each skilled trade, subcontracted labor cost, material cost and quantity, and total estimated hours for each activity. Rather than using a formal CMMS for tracking projects, Shipyard D uses a mostly internal and less formal method of tracking costs and schedule throughout their project based on the completed estimate. Similar to other shipyards, each repair project is assigned a project manager who is solely responsible for tracking the project and maintaining the schedule.

During the site visit, the shipyard representative interviewed stated that the shipyard has received multiple grants through the MARAD Small Shipyard Grant program for the purchase of newer, more advanced equipment and technologies including a floating dry dock. Of these new technologies, it was indicated that the purchase of a plasma cutter and waterjet cutting machine had the largest influence on increased labor productivity in the shipyard. Because these machines are automated, the process no longer has to be done manually by employees. Moreover, with the purchase of this new equipment, the shipyard no longer has to purchase and wait for material to arrive. Instead, they have the capability to manufacture these parts on-site, which has played a key role in reducing repair time and increasing productivity within the shipyard.

Along with the new equipment, the shipyard has also implemented and on time focused management strategy where each dry dock is planned for a scheduled amount of time and productivity in the shipyard is based on the number of vessels in and out that year. Another strategy to increase efficiency and productivity within the shipyard include a day with no breaks except a lunch break. The "no-break" strategy has worked well in the shipyard due to continual communication concerning deadlines and incentives offered to employees for finishing a project ahead of schedule. One incentive strategy used in the shipyard is an hourly bonus pool that accumulates hours when projects are completed ahead of schedule and with less man-hours than estimated. When the bonus pool reaches a certain level, each employee receives a bonus check as an incentive for meeting deadlines

Similar to many industrial operations, Shipyard D has also collaborated with a local technical college to develop a specialized apprenticeship program for the shipyard. The program is designed to help with employee retention as well as increase the skill level of shipyard employees. The apprenticeship program combines traditional classroom work with on-the-job

(OTJ) training. The apprentice trades offered by this program are welders, marine painters, marine pipefitters, machinists, electricians, riggers, and carpenters. At the conclusion of the program, the apprentice will earn a certificate in basic industrial work skills as well as an Associate Degree in general technology. Along with the apprenticeship program, Shipyard D also provides opportunities for employees already working for the company for advancement and promotion as well as opportunities to continue their education or further develop their skill set.

3.2.5 - Shipyard E

Although Shipyard E declined the invitation to work as a partner and provide specific operational data for this research, the shipyard did agree to a site visit with the research team. Shipyard E’s facilities encompass more than 100 acres in total and include approximately 240,000 square feet of covered buildings. Of the covered area, 115,000 square feet is dedicated to shipyard storage and shop/fabrication area. The shipyard has fully yard utility distribution systems including steam, compressed air, potable water, cooling water, and electrical power distribution. Shipyard E can accommodate vessels up to 875 feet in length, 150 feet in width, with a maximum draft of 30 feet. The shipyard is inclusive of three dry docks with a maximum capacity of 15,750 long tons, a marine railway with a maximum capacity of 1,300 long tons, a marine travelift capable of handling 1,0000 metric tons, and several various cranes capable of lifting up to 230 tons. Other features of the shipyard include five full service piers, two limited service piers, and two limited service wharfs. In addition to in-house repairs, Shipyard E also provides an outsource group that performs full service marine repair contracting to other shipyards.

During an interview with a shipyard employee, the employee stated that the shipyard has similar frustrations with manpower as other ship repair facilities. One of the main frustrations is a lack of manpower, which the shipyard employee relates primarily to a lack of training and employee retention. Because of this, the shipyard relies heavily on subcontracting to provide the necessary labor force required. It was also stated that labor is one of the shipyards primary issues with regard to efficiency. By not having the needed manpower, the issue influences downtime and in return decreases efficiency and productivity. In addition to subcontracted labor, at any given time, the shipyard employs approximately 100 temporary employees in the paint department due to the high levels of manpower required. In an attempt to provide a solution to the lack of manpower, Shipyard E partnered with a local technical college to develop an apprenticeship program. During the program student’s work full time at the shipyard earning competitive wages while also completing classwork. While the apprenticeship program is still in its early stages, representatives from the shipyard believe the program will be instrumental in employee retention moving forward.

3.2.6 - Planning and Scheduling

Ferries and their systems are major assets to the NCDOT, NCFS, and the millions of passengers who rely on them annually. Therefore, ferry maintenance is critical in order to meet the needs and requirements of these passengers. Moreover, the availability and preparedness of the ferry fleet is essential to long-term viability of the NCFS. The main objective of ship maintenance management is to maintain high availability of assets and the role of maintenance is to ensure the ferries are seaworthy and equipped to perform their specified role (Deris et al., 1999). The availability of ships is dependent on the effectiveness of implementing a preventative maintenance system (PMS) and the requirements for availability are met through significant investment in maintenance (Deris et al., 1999; Cullum et al., 2018). The role of a PMS is to provide standardization to the maintenance process from the planning phase through the execution phase and to provide a framework to assist with decision-making at the shipyard. While there are several components that make up a PMS, maintenance scheduling is considered one of the main factors (Deris et al., 1999). However, to understand the importance of maintenance scheduling, there must also be discussion pertaining to the maintenance planning process. This is because maintenance scheduling is a direct product of the maintenance planning process (De Boer, Schutten, & Zijm, 1997). Studies relating to planning efforts in the construction industry also include scheduling as a planning tool that is used as a part of the planning process and several studies have shown performance improvement with formal pre-project planning (Ghio, Valle, & Rischmoller, 1997; Menches, Hanna, Nordheim, & Russell, 2008; Oglesby, Parker, & Howell, 1989).

De Boer et al. (1997) developed a system to support decision making at a large ship repair and maintenance facility and identified three important elements of a decision support system: (1) process planning; (2) aggregate capacity planning; and (3) finite capacity scheduling. These elements can be understood as the main phases of the project planning process differentiated by the level of detail and objectives of each phase. Process planning is the first phase in the process and represents preliminary planning done well in advance of the execution of maintenance activities. Process planning determines current shipyard maintenance requirements and what maintenance activities or actions must be done (De Boer et al., 1997). Aggregate capacity planning is a more detailed, two step planning process undertaken once process planning is complete. As opposed to process planning, aggregate capacity planning establishes constraints, resource availability, durations, procedures, and project dates (De Boer et al., 1997). The final and most detailed phase in the planning process is finite capacity scheduling. During this phase, planning is done at the activity level. For each activity, resource requirements are established, activity relationships are developed, exact durations are determined, and a maintenance activity schedule is developed (De Boer et al., 1997). Table 4 summarizes the aforementioned planning process phases.

Table 4: Maintenance Planning Phases

Planning Phase	**Level of Detail**	**Planning Objectives**
Process Planning	Shipyard	• Shipyard Maintenance Requirements • Establish Maintenance Activities/Actions to be done
Aggregate Capacity Planning	Project	• Project Constraints • Resource Availability • Project Durations • Procedures • Project Dates
Finite Capacity Scheduling	Activity	• Activity Resource Requirements • Activity Relationships • Activity Durations • Maintenance Schedule

The planning phases discussed previously are only meant to serve as an example of the planning process and to illustrate the changes in planning objectives and level of detail from phase to phase. The maintenance planning and scheduling processes are different from organization to organization and dependent on their specific needs and management capabilities. Moreover, through investigation, it was observed that little to no formal project planning or scheduling takes place in the maintenance and repair facilities included in this study. Of the shipyards, only one, Shipyard B, uses a formal schedule for their repair projects. Shipyard B uses Microsoft Project to develop project schedules with integrated efficiency ratios to assist the project manager in maintaining and tracking the schedule. Shipyard D does not perform any formal planning or scheduling procedures; conversely, they use an internally developed system along with Microsoft Excel to create an estimate that is used by the project manager to track and maintain the schedule. The remaining two shipyards, Manns Harbor and Shipyard C, do not perform any formal planning or scheduling and rely solely on the shipyard superintendent to ensure projects are completed on time.

Even without formal planning or scheduling, the majority of shipyards under investigation report high levels of performance and on-time project completion. However, regardless of current stated performance levels, detailed formal pre-project planning provides several benefits that can be realized by improvements to project performance and reduced schedule overruns. Performing comprehensive planning prior to the commencement of work provides thorough knowledge and understanding of the entire project for those involved. In addition, any potential problems or difficulties that may arise on the project can be identified early, and plans to mitigate these potential problems can be developed. For example, during the process-planning phase, maintenance requirements for the project are identified and any repair activities that may require long-lead time parts can be planned for accordingly so that the procurement of materials does not cause delays to project. Performing pre-project planning allows all project and resource constraints to be identified. In addition to constraints, detailed planning also allows a detailed activity list to be developed. The development of a complete activity list aids in determination of activity relationships, durations, and sequence of work; which, when combined with constraints, provides the background information needed to create a detailed activity schedule for the project.

The intent of this section is not to discuss the systematic procedures and processes for creating a detailed maintenance schedule, nevertheless multiple different strategies for ship maintenance scheduling can be found in literature. De Boer et al. (1997) introduced a multi-project resource-constrained project scheduling system to support detailed ship repair planning. Deris et al. (1999) propose a method of ship maintenance scheduling by genetic algorithm and constraint-based reasoning. van Dijk et al. (2002) advocate that the critical path method (CPM) of project scheduling has several shortfalls for the ship repair industry and, as an extension of De Boer et al. (1997), proposed a multi-project approach with simultaneous consideration of time and shipyard capacity. Ahluwalia and Pinha (2014) assert that schedules based on Microsoft Excel or Microsoft Project software are stagnant in nature and often result in cost and schedule slippage as well as low throughput. As an alternative to these methods, Ahluwalia and Pinha (2014) suggest a decision support system aimed at maximizing system throughput and minimizing total project cost that is oriented towards day to day decision making and resource constraints. Additionally, Cullum et al. (2018) suggest a new risk-based scheduling technique for ship repair facilities that consists of two elements; a risk assessment followed by maintenance scheduling. These aforementioned methods are not inclusive of all the potential scheduling methods, they are only meant to provide examples of potential methods and to show the multitude of different approaches and techniques for developing detailed maintenance project schedules. Each method has its own unique set of advantages and limitations; therefore, selecting the best method for scheduling at ship maintenance and repair facilities must be done on an individual basis. The scheduling method selected for a particular operation must coincide with the organization's structure, goals, abilities, and maintenance objectives in order to be effective.

While it is easy to see the advantages of detailed planning and scheduling, the main drawbacks surrounding planning and scheduling deal with the need for expertise in scheduling and additional cost and time to complete these detailed planning measures. To complete detailed project pre-planning and scheduling, the organization must supply additional manpower outside of normal operations, which increases costs. Moreover, due to the complex nature of project scheduling, those involved must have knowledge and expertise in project management and scheduling. In addition, to complete intricate plans for maintenance projects a significant amount of time must be dedicated to these processes prior to the start of work. Despite the increased staffing requirements and upfront cost of implementing formal planning procedures, the benefits of implementing these measures can negate these upfront costs and in some cases even save money over the duration of the project. However, more importantly, implementation of formal planning and scheduling processes has been shown to improve project performance and to prevent cost and time overruns. Detailed plans ensure all aspects of the project are fully understood, ultimately resulting in a reduction of project uncertainty and a more accurate estimation of duration and cost. Furthermore, the detailed plans and schedules created during these planning processes are useful well after the start of the work. Plans and schedules developed before the start of the project can be used throughout the duration of work to monitor and track the progress of activities as well as make modifications to the original plan if the scope of work changes significantly. Lastly, if detailed plans are created, tracked, and updated throughout the course of the project, management can use these plans and schedules to build a historical database for reference on future projects and as a means of evaluating the performance of the facility over time.

3.3 - Operational Data Collection

For this research, data was collected directly from each organization participating in the study. Data was collected during visits to each shipyard, through interviews with shipyard representatives, through email communication with administrative personnel at the participating organizations, and from information provided on company websites. In addition to the qualitative data concerning shipyard technologies, capacities, organizational structures, and management strategies discussed in the previous section, historical vessel maintenance operations data was gathered from each shipyard for the purpose of performance and efficiency evaluation through quantitative analysis of shipyard operations by means of Data Envelopment Analysis (DEA). The maintenance operational data collected includes physical characteristics of the vessel under repair, maintenance and repair activities performed, trades that executed each activity, number of personnel working on each vessel, man-hours required to complete the repairs, and total refurbishment time in days to complete each repair project. Detailed discussion of specific data collected from each shipyard is provided in the following sections of this paper.

3.3.1 - Manns Harbor

The data for Manns Harbor was collected during the most recent visit to the shipyard on January 24, 2018. The data was downloaded directly from the SAP System using an IW47 transaction along with the assistance of the Administrative Assistant, the Marine Shipyard Superintendent, and the Marine Planner/Scheduler Supervisor. The data collected includes work order numbers, activities, trades, start and finish dates, man-hours, and employee identification information. An example of the data collected excluding employee names can be seen in Table 5. Additionally, prior to the latest visit, data was also collected concerning organizational structure, shipyard departments and trades, personnel hourly rates, and current shipyard employees.

The data provided from the SAP System follows the hierarchy shown below in Figure 3. The data starts with the Decision Making Unit, Manns Harbor Shipyard. It is then broken down by work order number, which includes vessel identification and date of the work order completion. Under each work order number, the data is divided into eight (8) individual work categories. The work categories are as follows: (1) Docking, (2) Hull Structure and Inspections, (3) Piping, (4) Machinery, Inspections, and Tests, (5) Operation Activities, (6) Electrical, (7) Paint, and (8) Technical. Each work category is broken down further into individual activities related to each category. All activities are identified by a unique activity code and description. For example, the activities included in Docking are 1000 – Docking, General; 1081 – Defueling Vessel; 1090 – Crane/Forklift and other services; 2000 – Hull, General; and 2010 – Dry-Docking. Individual activities are broken down by the trades involved in the completion of each activity. The trades are then grouped into Cost Centers or Shipyard Departments. The Cost Centers are FER Shipyard, FER Mechanics, FER Paint, and FER Welding. Finally, all employees in the Shipyard are grouped under the appropriate Cost Center. An example of the break down process from Activity to Employees is illustrated in Figure 4.

Table 5: Manns Harbor Data Example

Created On	Order	Activity	Cost Code	Act. Start	Act.finish	Act. Work
5/2/2016	82001001126	1000	7305	4/26/2016	4/26/2016	3
5/2/2016	82001001126	1000	7304	4/26/2016	4/26/2016	3
5/2/2016	82001001126	1000	7446	4/27/2016	4/27/2016	1
5/2/2016	82001001126	1000	7305	4/29/2016	4/29/2016	2
5/2/2016	82001001126	1000	7305	4/29/2016	4/29/2016	2
5/2/2016	82001001126	1000	7446	4/29/2016	4/29/2016	2
5/2/2016	82001001126	1000	7304	4/29/2016	4/29/2016	2
6/7/2016	82001001126	1000	7305	6/3/2016	6/3/2016	2
6/7/2016	82001001126	1000	7304	6/3/2016	6/3/2016	2
6/7/2016	82001001126	1000	7446	6/3/2016	6/3/2016	2
6/7/2016	82001001126	1000	7446	6/3/2016	6/3/2016	2
6/27/2016	82001001126	1000	7446	6/22/2016	6/22/2016	2
6/27/2016	82001001126	1000	7305	6/22/2016	6/22/2016	2
6/27/2016	82001001126	1000	7304	6/22/2016	6/22/2016	1
6/27/2016	82001001126	1000	7305	6/22/2016	6/22/2016	2

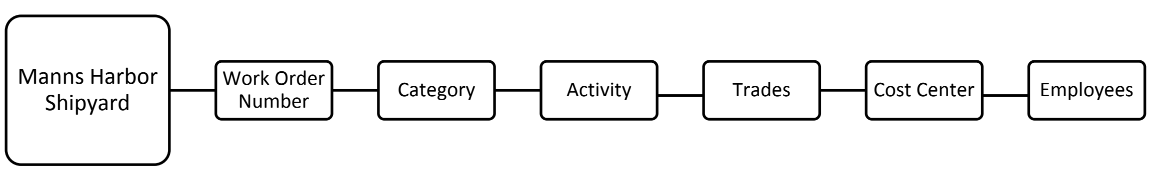

Figure 3: Manns Harbor Data Hierarchy

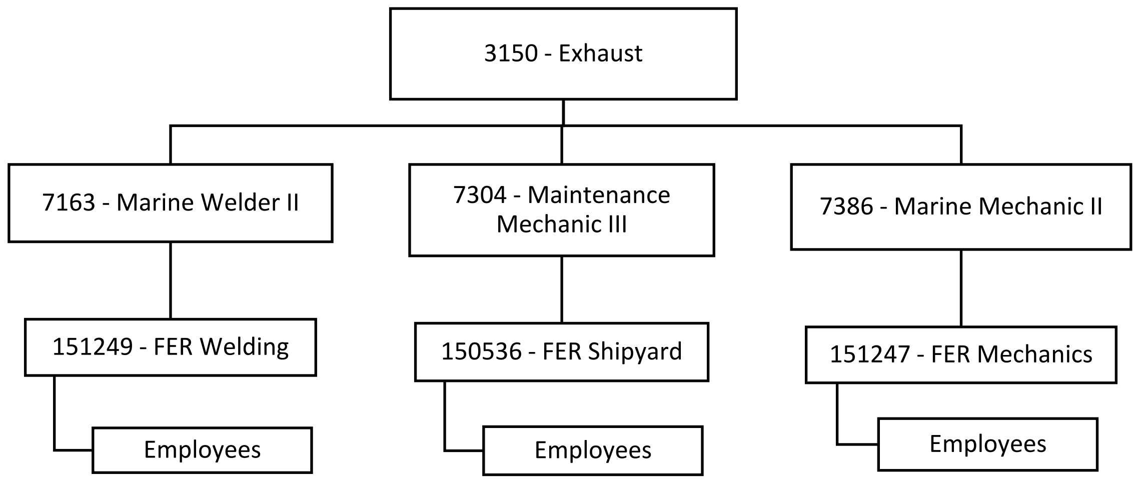

Figure 4: Manns Harbor Activity to Employees Hierarchy

3.3.2 - Shipyard B

Operational data for Shipyard B was collected following the visit to the shipyard on March 21, 2018. The data was provided to the researchers by the shipyard's Project Manager/Estimator in Excel spreadsheets through email communication. As previously mentioned, Shipyard B does utilize an Oracle-based Integrated Work Management System to track new ship builds, however the system is not currently used to track vessel repair projects. For repair projects, the shipyard utilizes spreadsheets to estimate as well as track cost and schedule throughout each project in a similar fashion to the IWMS procedures. However, unlike other shipyards, Shipyard B does not utilize a hierarchy or similar organizing structure to categorize their maintenance activities. Alternatively, Shipyard B tracks activities using a four-digit task identification number, therefore cost and time are charged directly to each specific task. In addition, Shipyard B also assigns a unique job number for each project undertaken. The job number is used to relate specific activities with a particular job in order to track schedule, labor, and cost for each project. An example of Shipyard B's project tracking method is shown in Figure 5.

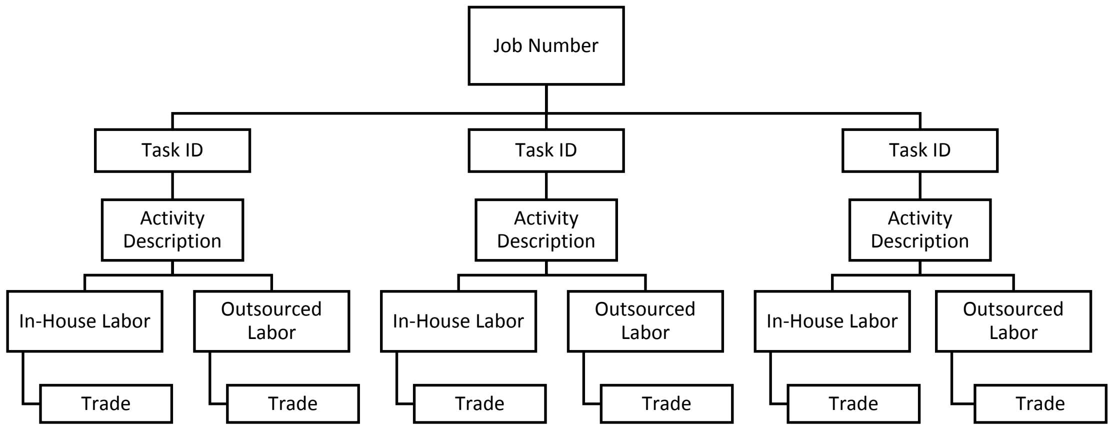

Figure 5: Shipyard B Data Tracking Example

Shipyard B provided the research team operational data ship repair projects similar in size and scope to those completed at Manns Harbor. The data collected from Shipyard B was provided in two separate parts, the first part being an invoice for each repair project and the second part being inclusive of all in-house labor as well as subcontracted labor charged to each project. Data provided in invoice spreadsheets is inclusive of the activities to be completed on the vessel with a task identification number, a description of the work to be done for each activity, the quantity of material required per activity, and a total cost for each activity. An example of the data provided in each invoice is shown in Figure 6. Data contained in the labor spreadsheets include the job number, four-digit task identification number, task name, date for work on each activity, the type of labor working on an activity (i.e. in-house or outsourced), the trade(s) conducting work for an activity, and the man-hours charged to the each activity. An example of this is shown in Table 6.

3400	Steering Gear			
	Disconnect rudder equipment in order to swing rudders full in order to remove propellers and shafts.			
	Retainer plates were removed in order to remove tailshafts.			
	Connect rudder and install retainer plates as original upon completion of installation of the tailshafts			
	and propellers.			
	Remove (15) bushings from the jockey bar, dead man and tiller arm. Fabricate and install (15) new			
	bushings.			
		Total:	**$ 7,521.16**	

Figure 6: Shipyard B Invoice Example

Table 6: Shipyard B Data Example

JOB#	Task ID	Task Name	Date	Trade Description	Stime Hrs	Otime Hrs	Total
2511053	1610	COMPETENT PERSON	14-Apr-07	DIR.ISL.WELDER/FITTER.OT.B	0	1	1
2511053	1610	COMPETENT PERSON	15-Apr-07	DIR.ISL.WELDER/FITTER.OT.B	0	1	1
2511053	1610	COMPETENT PERSON	15-Apr-07	DIR.ISL.WELDER/FITTER.OT.B	0	1	1
2511053	1610	COMPETENT PERSON	16-Apr-07	DIR.ISL.WELDER/FITTER	1	0	1
2511053	1610	COMPETENT PERSON	16-Apr-07	DIR.ISL.WELDER/FITTER	1	0	1
2511053	1610	COMPETENT PERSON	17-Apr-07	DIR.ISL.WELDER/FITTER	1	0	1
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.WKG LEADERMAN.OT.B	0	2	2
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.WELDER/FITTER	3	0	3
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.WELDER/FITTER	2	0	2
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.WKG LEADERMAN	2	0	2
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.MATERIAL PERSON	2	0	2
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.WELDER/FITTER	3	0	3
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.ISL.MECHANIC	0.5	0	0.5
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.OSL.WELDER/FITTER	2	0	2
2511077	2100	DRY DOCK AND LAUNCH	19-Jun-07	DIR.OSL.WELDER/FITTER	2	0	2

3.3.3 - Shipyard C

A visit to Shipyard C was conducted on December 19, 2017. Operational data was provided to the research team after the visit was complete. Data was received through email from the shipyard's Bookkeeper. Shipyard C, as previously mentioned, utilizes Intuit QuickBooks to track and manage both time and cost for their projects. However, prior to receiving the data, Shipyard C's Bookkeeper exported the operational data into Excel spreadsheet format. Operational data at Shipyard C is grouped into two categories, shipyard labor and subcontract labor. Because Shipyard C is a relatively small shipyard with a limited number employee and conducts in-house work only on hull related activities, no further categorization of operational data is done.

Data from Shipyard C was received in three spreadsheets. The first spreadsheet was inclusive of personnel information including employee identification and job titles for each employee. The second spreadsheet included a list of maintenance and repair activities performed at the shipyard. Each activity is represented by a unique activity identification number, a description of the activity, and an identifier that represents the type of labor used to complete the activity. An example of this data is shown in Table 7. The third spreadsheet contained operational data of work similar in scope to the projects completed by the NCFS. Operational data was inclusive of the activities completed on each project, a description of those activities, identification of employees who completed work for each activity, the hours worked on each activity, and the date the work was completed. A visual example of this data is shown in Table 8.

Table 7: Shipyard C Activity List Example

Activity
010005 HR HULL JIG
010005 OV HULL JIG
010010 HR Cutting General
010010 OV Cutting General
010011 HR Sandblast and prime
010011 OT Sandblast and prime
020009 HR BURNING HULL
020009 OV BURNING HULL
020010 HR Hull General
020010 OV Hull General
020011 HR EQUIP. OPERATOR
020011 OV EQUIP. OPERATOR
020012 HR Hull Fitting
020012 OV Hull Fitting
020013 HR Hull Welding
020013 OV Hull Welding

Table 8: Shipyard C Operational Data Example

Date	Employee ID	Activity	Hrs
03/16/2018	19534	020010 HR Hull General	(4.75)
01/19/2018	19403	020010 HR Hull General	(2.50)
01/19/2018	19422	020016 HR Hull Cleaning	(2.00)
01/12/2018	19401	020016 HR Hull Cleaning	(1.00)
01/12/2018	011218B	258500 (SUB - PAINTING)	(1.00)
01/12/2018	011218B	258500 (SUB - PAINTING)	(1.00)
01/10/2018	8333	251000 (SUB - ELECTRIC)	(1.00)
01/05/2018	ACH	020010 HR Hull General	(1.00)
01/05/2018	010518	258500 (SUB - PAINTING)	(1.00)
01/05/2018	010518	258500 (SUB - PAINTING)	(1.00)
12/29/2017	19368	020010 HR Hull General	(1.25)

3.3.4 - Shipyard D

Data collected from Shipyard D was provided during the visit to the facility conducted on May 21, 2018. Projects at Shipyard D are estimated and tracked through utilization of spreadsheets. Operational data for Shipyard D was provided to the research team by the shipyard's Sales and Marketing professional. The data was received in the form of a printed hard copy of an Excel spreadsheet, which was later manually input into an electronic spreadsheet. The data collected includes work order number, vessel characteristics, shipyard departments, activities and activity categories, man-hours for each department per activity, subcontractor information, and refurbishment cost including in-house labor, subcontracted work, and materials cost. An example of the data received from Shipyard D can be seen in Figure 7; however, cost and pricing information are omitted at the request of the shipyard.

		DEPARTMENT HOURS								
Act. #	**Activity**	**Hull**	**Elec.**	**Mach.**	**Pipe**	**Carpentry**	**Rig**	**Labor**	**Paint**	**Subtotal**
2	**SERVICES**	**120**	**28**		**24**		**24**	**80**		**276**
2.1	Gangways		16				16			32
2.2	Shore Power Connection		8				8			16
2.3	Shore Power Consumption									
2.4	Temp. Lighting									
2.5	Potable Water Connection				8					8
2.6	Potable Water Consumption									
2.7	Fire Main				8					8
2.8	Sewage Connection				8					8
2.9	Telephones		4							4
2.10	Garbage									
2.11	Oily Bilges							16		16
2.12	Cranage for Waste, Stores and Spares							32		32
2.13	Safe Entry and Safe Working Certificates							32		32
2.14	Docking Plugs	120								120

Figure 7: Shipyard D Operational Data Example

Vessel maintenance and repair projects at Shipyard D are organized, estimated, and tracked using a basic hierarchical system shown in Figure 8. The hierarchy begins with a unique work order number given to each vessel when it arrives at the shipyard. Each work order is then broken into activity or maintenance categories. Activity categories are used to group similar activities based on the type of service provided, specific areas of the vessel, or operational systems and equipment on the vessel. In total, nine categories are used to group activities. These categories include services, docking, propulsion equipment, hull cleaning and coating, hull equipment, valves and piping, hull and deck repairs, galley and accommodation spaces, and oil-fired boilers. Each category is inclusive of all maintenance activities to be done on the vessel related to that specific category. Each activity is then tracked in two separate manners, labor (i.e. man-hours) and cost. Labor is charged to each activity on an individual shipyard department level including subcontracted labor. This allows the shipyard to track the total hours each department worked on a particular activity. This can be seen in Figure 7 above. Finally, costs for each activity are broken down into three levels, shipyard labor, subcontractors, and materials.

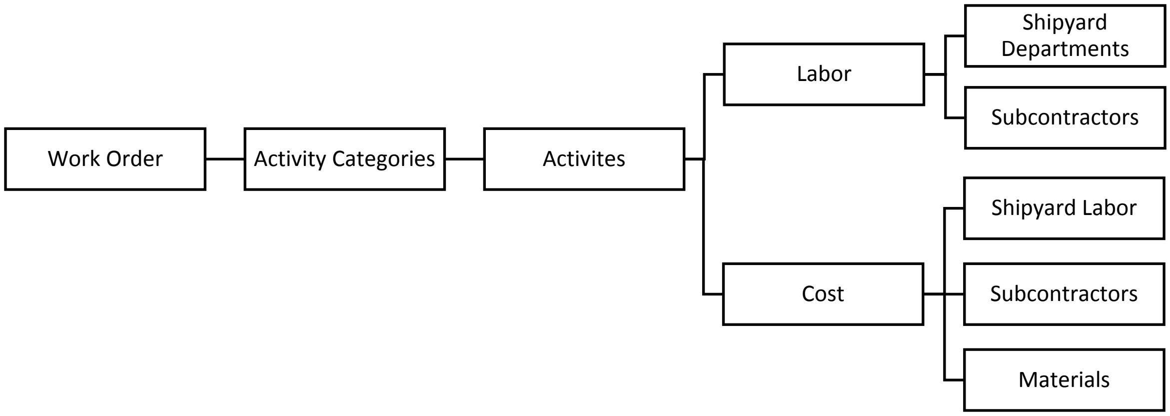

Figure 8: Shipyard D Data Hierarchy

3.3.5 - Data Organization

In order to perform the efficiency analysis of shipyard maintenance operations, the data collected from each shipyard must be categorized and organized in a similar fashion. To organize the data, the hierarchical framework utilized by Manns Harbor Shipyard (Shipyard A) was used as a baseline. The data collected from the other participating shipyards was broken down and categorized using the activities categories employed by Manns Harbor. The activity categories applied include docking, hull, piping, machinery, operation activities, electrical, paint, and technical. Organization of data was completed in a two-step process. The first step of the organizational process involved developing an activity list for each shipyard. Once an activity list was developed for each shipyard, the second step involved grouping the maintenance activities under the aforementioned categories. Organization of the data in this manner allowed labor production rates for each maintenance category to be developed and compared amongst participating shipyards.

3.4 - Assessment Methods

The assessment of the productivity and efficiency of Manns Harbor Shipyard was completed through utilization of DEA. The data used to complete DEA includes internal and external variables related to production in the ship repair industry developed through thorough investigation of ship repair operations and related literature to identify the factors that affect the production process. In addition to the DEA assessment, a qualitative assessment methodology was also developed to evaluate qualitative characteristics of ship repair production. Several studies related to performance evaluation of ship repair and shipbuilding operations have used a qualitative assessment of shipyard operations to either develop a qualitative factor for use in DEA, to develop an additional means of operation evaluation for providing performance improvement recommendations, or as a means of validation for the results provided by DEA (Alhouli, 2011; Guofu et al., 2017; Park et al., 2014; Pires & Lamb, 2008). The purpose of the qualitative evaluation in this study is to assess operations based on important realistic factors identified by industry experts in order to compare and validate the results presented by DEA and for the development of a qualitative performance variable used in the DEA assessment. Once each assessment is conducted, the results of each analysis will be compared to determine whether the efficiencies represented by DEA match the results of the qualitative analysis. Visual representation of this process is shown in Figure 9.

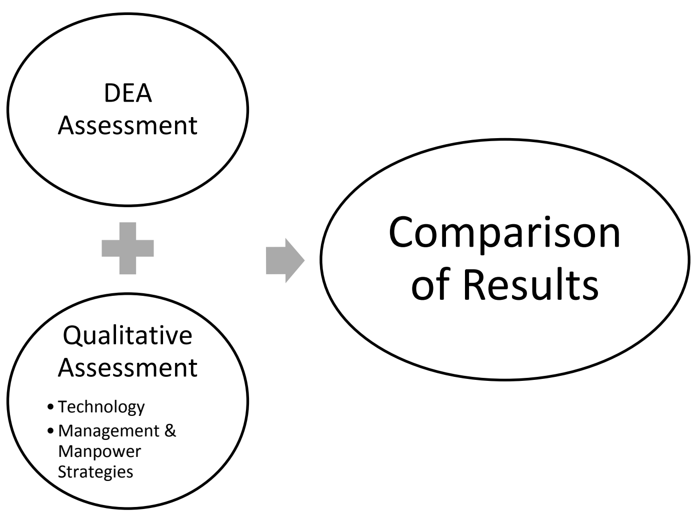

Figure 9: Overview of Assessment Methodology

3.4.1 - Qualitative Assessment

Qualitative assessment of shipyard operations was completed using a three-step process. The first step of the methodology involved visits to each participating shipyard. During these visits, interviews were conducted with industry experts at each shipyard. Interviews with experts involved asking questions related to shipyard operations, shipyard productivity, manpower types and utilization, as well as efficiency strategies utilized by each shipyard. In conjunction with these interviews, the research team also made general observations about each shipyard's operations including technologies, equipment, day-to-day tactical operations, management strategies, organizational structure, planning and scheduling measures, and project tracking methods and procedures. Once visits and interviews to each shipyard were completed, notes recorded during individual visits were compiled in order to categorize observations into qualitative components. Summaries of these observations are provided in a succeeding section of this report titled Facilities Summaries – Qualitative Review. Two components were developed for the qualitative analysis, the first component is Technology and the second component is Management/Manpower Strategies. These components were developed based on the most important qualitative factors related to shipyard productivity and efficiency identified by industry experts.

The Technology component is inclusive of two subcategories, Advanced Machinery and Computerized Maintenance Management System (CMMS). The first category of Technology, Advanced Machinery, pertains to evaluation of each shipyard based on the machinery and equipment used in their operations. It was observed that some shipyards employ advanced technologies, not utilized by most shipyards, which has significantly improved the performance of their operations and reduced the amount of time a vessel is dry-docked for repairs. Specifically, these advanced technologies include new robotic paint-blasting slurries, plasma cutters, waterjets, and floating dry docks. Assessment of this category is done by determination of the use and quantity of advanced technologies utilized by each shipyard. The second subcategory of the Technology component, CMMS, is associated with the use of computerized software to manage and track repair projects at the shipyard. It is assessed first by determination of use in each shipyard. Once the use of a CMMS is determined, the category assesses the CMMS based on the level of design and use for ship repair projects specifically.

The second component of the qualitative assessment, Management/Manpower Strategies, is comprised of five subcategories related to strategies employed by the participating shipyards aimed at increasing operational performance. The five categories included in the Management/Manpower Strategies component are Organizational Structure, Planning and Scheduling, Efficiency Strategies, Apprenticeship Program, and Outsourced Labor. The Organizational Structure category is related to the use of specialized personnel within the organization for project management. Industry experts indicated that the use of a project management role within several organizations has significantly improved repair project performance, created a single point of responsibility for ensuring projects are completed on time, and significantly reduced the management responsibilities of field personnel within the shipyard. The second category, Planning and Scheduling, relates to the use of formal procedures for planning, estimating, and scheduling ship maintenance and repair projects. This category is evaluated based on whether the shipyard has a set of formal procedures as well as the level of detail of these procedures. The purpose of this category is to determine if the use of formal planning and scheduling procedures influences shipyard performance. Efficiency Strategies, the third category, is related to specific strategies implemented by management for the sole purpose of improving efficiency and productivity within the shipyard. It was observed that some of the participating shipyards have implemented strategies designed to improve their overall efficiency and productivity. These strategies are inclusive of strategies directly related to efficiency improvements as well as incentive strategies aimed at increasing the productivity of employees by providing incentives for high performance. This category is assessed by evaluating if a shipyard employs such strategies and the quantity/detail of strategies implemented. The fourth category, Apprenticeship Program, is related to employee retention within a shipyard as well as the skill level of the employees. Observation along with information gathered through interviews indicated that employee retention is a significant problem within shipyards, and as a means of combating this problem, apprenticeship programs have been developed for the purpose of employee retention as well as increasing the skill set of employees within the shipyard. This category is evaluated by determining if each shipyard utilizes an apprenticeship program and by evaluation of the requirements and certifications of the program. The final category of Management/Manpower Strategies, Outsourced Labor, assesses the use of outsourced labor utilized by each shipyard. Assessment of the Outsourced Labor category is done first by determination of the shipyards use of outsourced labor and secondly by evaluation of the availability of outsourced labor and the level of which outsource labor is utilized on vessel repair projects. Figure 10 is provided as a graphical representation of the categorization of the components utilized in qualitative assessment.

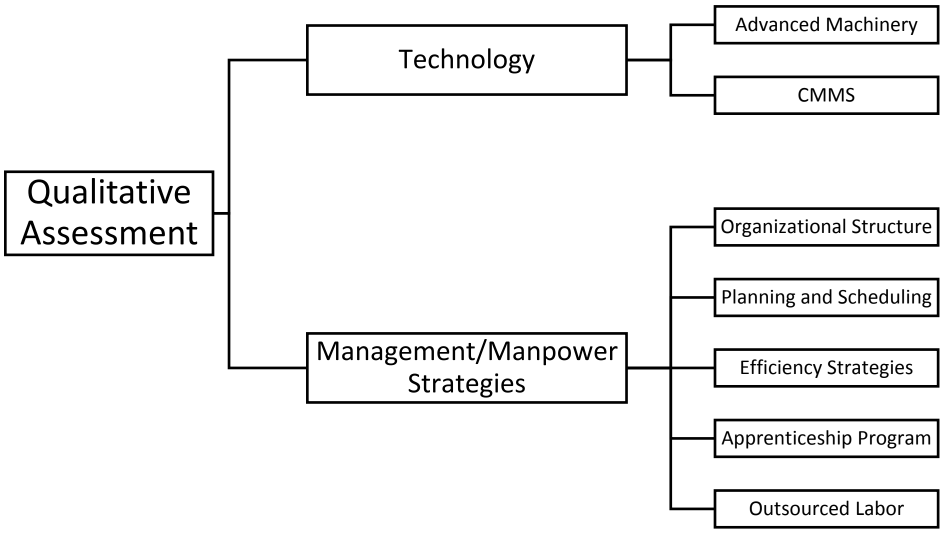

Figure 10: Qualitative Assessment Components and Subcategorization

The second step of the qualitative assessment methodology is to develop a matrix to be utilized for assigning implementation levels to each shipyard for all qualitative assessment components and subcategories. The matrix utilized for assigning the level of implementation for each qualitative factor can be seen in Table 5. To score each shipyard, a score was given for each shipyard based on the level of implementation for each specific category. A scale system of one (1) to five (5), with a score of one (1) being little to no implementation and a score of five (5) being high implementation, was utilized to score each shipyard's level of implementation on a per category basis. The ranking given to each shipyard was based on the aforementioned criteria discussed for each category quantified using information provided through organization websites and information gathered during site visits and interviews.

For the Advanced Machinery category, the shipyards were scored based on the quantity of advanced technologies utilized by the shipyard. Scoring of the CMMS category was done by determining whether the shipyard utilizes such software and to what level the software is specialized for ship repair operations. Organizational Structure scoring was determined by the use of a project management role within the shipyard and the quantity of project managers utilized within the organization. Scoring for Planning and Scheduling was done based on the use of formal planning and scheduling procedures and the level of detail in which planning and scheduling is done. The Efficiency Strategies category was scored by the quantity of specific efficiency strategies utilized by each shipyard as well as incentive strategies implemented by the organization. The scoring of shipyards for Apprenticeship Program was determined by the use of a program and the specified outcomes of the program. Finally, the scoring for Outsourced Labor evaluated on the level of outsourcing used and the availability of subcontracted resources for each shipyard. After the completion of assigning scores, a total score for each shipyard was calculated by summing the total number of points received by each shipyard. The total score was utilized to rank the shipyards from one to five, with one being the lowest ranking and five being the highest ranking based on these qualitative factors. The completed matrix for qualitative assessment of the shipyards can be seen in Table 9.

Table 9: Qualitative Assessment Matrix

Qualitative Assessment Component	MH	SY B	SY C	SY D	SY E
Technology					
Advanced Machinery					
CMMS					
Management/Manpower Strategies					
Organizational Structure					
Planning and Scheduling					
Efficiency Strategies					
Apprenticeship Program					
Outsourced Labor					
Total Score out of 40:					

As previously mentioned, in addition to providing analysis of shipyard operations based on qualitative factors, the qualitative assessment is also utilized in the development of a qualitative shipyard factor variable for use in the DEA quantitative evaluation of shipyard operations. In a similar study involving the establishment of performance targets for shipbuilding companies, Pires and Lamb (2008) utilize a similar qualitative factor they called Industrial Environment as an input to DEA for their analysis. Pires and Lamb (2008) state that in addition to physical attributes related to the facility, shipyard performance depends on the industrial environment of the facility, which is inclusive of factors related to organizational structure, workforce makeup, and strategies implemented within each shipyard. To develop this qualitative factor, Pires and Lamb (2008) utilize the Analytical Hierarchy Process to assign weights to each component.

This research will utilize a similar process in the development of a qualitative variable for DEA. A ranking system will be developed based on the qualitative information gathered and weights will be assigned to each component based on its relative importance to the production process of ship repair operations. A pairwise comparison will be used to develop and assign weight factors for the qualitative criteria under evaluation. The advantage realized through the utilization of this process would be the understanding that the qualitative factors and weightings would provide more value for DEA versus a qualitative variable based simply on a summary of scores for each shipyard. Detailed discussion of the process for development of the qualitative variable is provided in the Quantitative Assessment section of this paper.

3.4.2 - Quantitative Assessment

Quantitative assessment of the maintenance and repair operations at Manns Harbor Shipyard was completed by means of Data Envelopment Analysis (DEA). Two separate analyses were completed to assess the repair operations. The first analysis involves an external DEA assessment in order to compare Manns Harbor operations with other ship repair facilities. The purpose of the external analysis is to determine if Manns Harbor repair operations are efficient when compared to similar operations of other shipyards. The external analysis is aimed at evaluating efficiency from a holistic approach from the shipyard level on a per work order or dry-dock basis. In general, the goal of the external analysis is to determine if Manns Harbor Shipyard is completing vessel repair work in an efficient manner. The second part of the quantitative assessment utilizes DEA to assess the efficiency of internal operations at Manns Harbor. The internal analysis is aimed at determining the efficiency with which the Manns Harbor's trade departments complete work on a work order to work order basis. The internal analysis evaluates Manns Harbor's repair operations from a more detailed, departmental level for the purpose of determining if the their current planned refurbishment times are realistic in nature and, if not, determine a more realistic timeframe for planned refurbishments. Moreover, the internal analysis will allow any potential internal inefficiencies to be identified so that recommendations for prospective corrective action to increase efficiency of those departments or internal repair operations as a whole can be made.

3.4.2.1 - Computer Support for DEA

As previously stated, DEA is a non-parametric, linear programming based mathematical optimization method used to assess the efficiency of a decision making unit (DMU) (Bröchner, 2017). Therefore, models can be built in Excel with the utilization the Solver tool to solve many various DEA models for a multitude of applications and data sets. However, with large data sets, this can become a tedious process because DEA requires a separate linear programming problem with different objectives and constraints to be solved for each DMU in the data set (Ozbek, 2007).

Moreover, this method requires advanced and in-depth knowledge of linear programming languages making the utilization of DEA less intuitive and difficult to understand for non-technical audiences. As a result, following the trend of advancement and expanded use of DEA, software developers have created software programs that can quickly provide solutions to DEA problems regardless of the size of the data set. The creation of these advanced DEA modeling programs have made the process of DEA more user friendly and significantly less time consuming.

While there are many various software programs available to carry out the DEA process, the software program utilized in this research is Performance Improvement Management Software (PIM-DEA). PIM-DEA was chosen because of its user-friendly interface, its ability to handle data sets of varying sizes, and its ability to produce multiple graphical representations of the results. PIM-DEA allows data to be either manually input into the software or directly imported from Excel. Additionally, PIM-DEA allows for multiple variations of DEA models to be developed and carried out simultaneously. This provides several advantages with respect to identifying sources of inefficiencies amongst DMUs. Organizations conducting work in the ship repair and maintenance industry are essentially service providers, therefore production characteristics of these operations are often difficult to determine or unknown all together. The utilization of PIM-DEA allows for fast and easy alterations to the DEA model(s) and production variables, ultimately allowing the best representation of actual maintenance and repair operation to be identified. Accurate representation of the maintenance processes and inclusion of relevant factors related to productivity or production are essential to accurately identifying inefficiencies and providing recommendations for improvement.

3.4.2.2 - External Analysis

The external analysis to compare the overall efficiency shipyard operations is inclusive of data from Manns Harbor as well as data from the three participating shipyards. Due to the data available and the limited number of shipyard willing to participate, the analysis could not be completed using shipyards as the DMUs. Therefore, to satisfy the requirements of DEA, for this analysis, the DMUs under investigation will be individual work orders for dry-dock repairs from each shipyard. In total, this analysis will include 15 DMUs. Of the 15 work orders under evaluation, nine are from Manns Harbor, four are from Shipyard B, one is from Shipyard C, and one is from Shipyard D. The data set for external analysis was limited to the information that each participating shipyard was willing to provide. However, despite the limited data set, accurate discriminatory power is provided, as there is at least twice the number of DMUs as there are input and output variables (Golany & Roll, 1989). Moreover, due to the homogeneity requirement amongst DMUs, the assumption is made that similar work was completed on each work order using similar equipment and processes. The complete list of DMUs under evaluation in the external analysis can be seen in Table 10.

Table 10: External Analysis DMU List

DMU (Work Order)	Shipyard
A1	Manns Harbor
A2	Manns Harbor
A3	Manns Harbor
A4	Manns Harbor
A5	Manns Harbor
A6	Manns Harbor
A7	Manns Harbor
A8	Manns Harbor
A9	Manns Harbor
B1	Shipyard B
B2	Shipyard B
B3	Shipyard B
B4	Shipyard B
C1	Shipyard C
D1	Shipyard D

The understanding that there are numerous factors, both directly and indirectly related to production, that determine productivity is essential when performing studies on service related industries. In the traditional sense, productivity measurement has been defined as a method of calculating an output to input ratio and comparing this ratio over two or more periods of time (Lamartin, 1980). In spite of its seemingly simple nature, productivity measurement and performance evaluation of service related industries, such as ship maintenance and repair, is a complex process due to the unique characteristics of the production process. Moreover, during a visit with Shipyard E, an industry expert emphasized that production parameters are more difficult to establish for ship refurbishment projects as oppose to shipbuilding projects because the amount of work and the types of repair work are very different from vessel to vessel. In the ship repair industry, shipyards provide a service to their customers rather than a product. Likewise, productivity is measured by the resources or inputs consumed to provide that service, which, in many cases, the main resource consumed to provide these services is man-hours. The problem arises when productivity measures are based solely on the labor required to provide vessel repair services. This is because productivity measures are partial when based on single indicators because they do not take into account the entirety of factors that have an influence on production (Rabar, 2015). Additionally, quantification of output is difficult in service industries. Unlike a manufacturing setting where output is easily quantifiable, quantifying the amount of service provided is not as instinctive. In the ship repair industry, output is generally quantified by the number of days required to complete a vessel or some other measure of time. While refurbishment time can be used to quantify output, time alone does not provide an adequate means of determining productivity.

The problem of performance measurement in the ship repair industry is further complicated once the discipline is evaluated in its entirety. Like other businesses, the ship repair industry is complex field comprised of multiple components, systems, and factors that, either individually or when combined with other elements, affect the productivity and performance of individual facilities. Additionally, an immense amount of diversity exists across the industry in terms of organizational models, shipyard characteristics and capabilities, organizational processes, and shipyard output patterns (Pires & Lamb, 2008). This diversity further complicates performance measurement because the individual characteristics and capabilities of ship repair facilities must be accounted for in these measurements. Consequently, productivity and performance of these facilities cannot be evaluated based solely on the physical resources, or inputs, required to provide a service, or output but must include general production influencers (Pires & Lamb, 2008). For that reason, production parameters used as input and output variables in the DEA model for efficiency evaluation of shipyard operations must take into account all relevant production influencers in order to provide accurate and effective results. Identification of these influencers requires thorough knowledge of the ship repair process and pragmatic investigation into realistic operations.

Input and Output Variables

To identify all relevant production influencers accurately, the research team conducted visits to ship repair facilities, held in-depth interviews with industry professionals, and extensively reviewed literature relevant to these operations. The production influencers, or DEA model inputs and outputs, for the external analysis are inclusive indices relating to shipyard capacity, shipyard employment levels, shipyard technology levels and operational strategies, labor productivity, and refurbishment time. These production parameters were selected based on their relevancy to production in the ship repair industry, availability and accessibility of data, measurability, and quantification. Moreover, these production characteristics were chosen in a manner to ensure that the results of the analysis would provide relevant, understandable, comprehensive, and useful information for the NCDOT and NCFS regarding their current operations, performance targets, as well as short and long-term planning of staffing and scheduling needs. Input and output variables chosen as production parameters for the external analysis can be seen in Table 11. A completed table of input and output variables calculated for each shipyard will be presented in the results section of this report.

Table 11: External Analysis Input and Output Variables

	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

Shipyard Capacity

As previously stated, the physical characteristics related shipyard capacities vary significantly from facility to facility. With regard to the shipyards in this study, the size of the shipyards as well as the drydocking capabilities vary drastically based on the shipyard size classification. Moreover, these characteristics have a direct impact on the quantity and type of work a shipyard can undertake which affects shipyard production. During shipyard visits, it was evident that size of the shipyard directly correlates with quantity of work and levels of production. This is also supported extensively in literature related to performance measurement of shipyards. In a report on establishing shipbuilding performance targets, Pires and Lamb (2008) state that shipyard capacity impacts the productivity and building time of shipyards. In their DEA model, Pires and Lamb (2008) utilize shipyard capacity, expressed as total erection area, as an input to their DEA model. Chudasama (2010) utilized shipyard capacity variables expressed in tons and maximum length of vessel as inputs into a DEA efficiency analysis of shipyards stating that these variables directly contribute to the operational activities of shipyards. In their study, Guofu et al. (2017) indicated that facilities and equipment are input factors that affect the performance of shipbuilding entities. Additionally, Ok and Feng (2017) applied total dock length, total area of docks, and total weight capacity of docks as inputs into their DEA evaluation of Chinese ship repair facilities asserting that these variables have the most direct impact on operational efficiency.

In this study, shipyard capacity will be expressed as a composite index, comprised of maximum drydocking capacity in gross tons, length and width of vessel. The shipyard capacity index was calculated by normalizing the shipyard capacity data for each of the capacity categories. An average of the three normalized capacities was taken and multiplied by a factor of 1000 to develop the shipyard capacity input for each shipyard.

Number of Employees

In shipyard operations, the main resource consumed to provide maintenance and repair services is employee labor. In other words, labor is a major input utilized to provide repair services or produce output in a shipyard. Therefore, the efficiency of a shipyard can be expressed as how well employee labor is expended to repair or refurbish a vessel. Consequently, employees have a major influence on shipyard productivity and operational efficiency because they are a direct input required for production in ship repair facilities (Ok & Feng, 2017). In literature, number of employees has been utilized frequently as an input to DEA models for similar studies. Chudasama (2010), Rabar (2015), and Ok and Feng (2017) all utilized number of employees as a direct input into DEA. Pires and Lamb (2008) included number of employees as a part of a productivity index utilized as an input for DEA. Guofu et al. (2017) indicate that labor is a direct input of shipyard operations as a part of their study on shipbuilding efficiency. Furthermore, in a study on the efficiency of Chinese ship repair facilities, Ok and Feng (2017) state that the inclusion of employment levels has an effect on the efficiency of shipyards because employment levels vary with the size of shipyards.

Number of employees will be utilized in this study as an input variable because of the direct correlation to shipyard production as well as the significant variation in employment levels amongst shipyards under evaluation. The number of employees for each shipyard is inclusive of only in-house full-time employee labor and is calculated based on the operational data provided by each shipyard at the time it was received.

Qualitative Factor

As mentioned previously, in addition to factors directly related to the production process, productivity and efficiency of any operation is also influenced by various indirect factors. In shipyards, levels of technology as well as managerial strategies of the shipyard affect the way operations and activities are carried out (Ok & Feng, 2017). Guofu et al. (2017) suggest that shipyard production efficiency is the combined effect of all production, technology, and management activities. Likewise, Pires and Lamb (2008) indicate that technological and managerial capabilities are influential to the competitiveness and productivity of a shipyard. In addition, they also state that the industrial environment of a shipyard has an effect on shipyard performance. In their study, Pires and Lamb (2008) utilized an industrial environment index as an input to DEA to represent the various qualitative factors related technological and managerial aspects of shipyard operation. However, because these factors cannot be easily changed by shipyards, industrial environment index was utilized as a nondiscretionary variable for DEA.

This study will employ a similar index based on the information discussed in the qualitative assessment. As discussed previously, the qualitative factor utilized as in input for DEA is centered on two main qualitative categories, Technology and Management/Manpower Strategies along with their accompanied subcategories. In order to develop a qualitative variable from the scores received for each category for the participating shipyards, a pairwise comparison was utilized to develop weights for each subcategory. Pairwise comparison allows each category to be compared to each of the other categories as a means of determination of which category has a greater amount of importance or effect on shipyard productivity. In other words, pairwise comparison allows the qualitative variable to more accurately represent the qualitative factors of each shipyard based on the relative importance of each qualitative category utilized. To complete the pairwise comparison, a survey was sent out to industry professionals in order to evaluate the importance of each qualitative category to shipyard production. The experts were asked to rank each of the variables from based on level of importance to productivity in the ship repair industry. Rankings for each variable were given using an index of one through seven (1 – 7), this index can be seen below in Table 12. Ranking provided through the survey were used in the pairwise comparison to develop relative weights for each of the qualitative factors under evaluation. A qualitative factor for each shipyard was then developed first by multiplying the score the shipyard received in each category by the relative weight for that category and then summing the weighted scores of each category to develop a total qualitative factor score. The total qualitative factor score was then multiplied by 1000 to develop the qualitative factor variable for use as an input to DEA.

Table 12: Survey Ranking Index

Numerical Value	Description
1	Least important
2	Slightly more important
3	Moderately important
4	Moderately to strongly important
5	Strongly important
6	Very important
7	Most important

Labor Productivity

Output of shipyards is typically represented by measures such as number of vessels delivered, delivered tonnage, or annual revenue. However, because of limited data availability, the inclusion of both public and private shipyards and the variance in shipyard size and scope, measures such as this are not feasible. Alternatively, labor productivity has been utilized in similar studies to represent shipyard output (Guofu et al., 2017; Pires & Lamb, 2008). Labor productivity can be used to represent ship repair output because it is directly related to the output patterns of a shipyard (Pires & Lamb, 2008). Moreover, labor productivity is an indicator of shipyard operational efficiency (Guofu et al., 2017).

While labor productivity can be used as a performance indicator, calculation of productivity must take into account the size and type of vessels under repair. Therefore, a common unit of measurement that includes these factors must be used to calculate labor productivity rates. Literature related to labor productivity in shipyards suggests using compensated gross tonnage (cgt) as the common unit of measurement (Guofu et al., 2017; Pires & Lamb, 2008; Rabar, 2015). CGT is a unit of measurement originally developed for shipbuilding activities to provide a common means to quantity the work required for various vessel types (OECD, 2017). CGT is calculated using the formula $cgt = A * gt^{B}$, where A is a factor that represents the type of vessel, gt is the gross tonnage of the vessel, and B is a factor representing the influence of ship size (OECD, 2017). Because some of the operational data provided by shipyards involves work on vessels other than ferries, cgt was utilized in this study as the unit of measurement to provide a means to compare different vessel types.

Similar to the aforementioned studies, labor productivity in this study will be expressed as man-hours per compensated gross ton. Labor productivity is calculated based on the total hours worked on each repair project. However, because labor productivity will be utilized as an output in the DEA model, the inverse of the calculated productivity rates must be utilized in the analysis so that an increase in labor productivity equates with an increase in performance.

Refurbishment Time

Refurbishment time or the time the vessel is dry-docked for repairs is a critical factor in determining the competitiveness of a shipyard. Moreover, the competitive potential of a shipyard is dependent on time to complete repairs, and time for repairs is severely dependent on shipyard performance (Pires & Lamb, 2008). This is especially important with regard to Manns Harbor. The amount of time a ferry is in the shipyard is crucial the NCDOT and NCFS because of the stringent maintenance requirements for these vessels. Each ferry owned and operated by the NCFS must be dry-docked two times every five years. Therefore, the refurbishment time is a critical factor for their operations and is key indicator of operational performance. However, for this study, it should be mentioned that refurbishment times can vary significantly from shipyard to shipyard and is related to the capacity, equipment, technology, and processes of each individual shipyard.

In a similar study, Pires and Lamb (2008) utilized a similar factor to represent the output of shipbuilding facilities called building time. Refurbishment time in this study will calculated based on the days a vessel was dry-docked from arrival to departure. Similar to labor productivity, because refurbishment time will be utilized as an output for DEA, the inverse of refurbishment time must be utilized in the analysis. This is because a reduction of days in the shipyard equates to an increase in shipyard performance. Refurbishment time in this study is calculated in days, and represents the total time the vessel was dry-docked in the shipyard from the start of work to the departure of the vessel.

DEA Model Selection

For the external analysis of shipyard operations, DEA will be carried out using both the CCR and BCC envelopment models. As discussed in the literature review section of this paper, envelopment models are used to establish a best practice frontier or to identify best practice DMUs. The difference between the CCR and BCC models relates to the returns-to-scale (RTS) type utilized in each model. The CCR model uses a constant returns-to-scale (CRS) and the BCC model utilizes a variable returns-to-scale (VRS). The efficient frontier created through use of a CRS is linear and assumes changes to inputs result in proportional changes to outputs. Alternatively, the efficient frontier created by a VRS is inclusive of three individual elements: the CRS surface, the non-increasing RTS surface, and the non-decreasing RTS surface. The significance of utilizing a VRS is that there is no assumption of proportionality between inputs and outputs, and changes to inputs can result in non-proportional changes in outputs. Both models are utilized for this analysis because determination of the appropriate RTS type to use for shipyard performance is unknown since the exact production characteristics and output patterns are difficult to determine with certainty.

Use of both the CCR and BCC models also allows scale efficiency (SE) to be calculated. Calculation of SE allows the sources of inefficiencies to be better identified. In other words, SE allows determination of the cause of inefficiencies to be related to either inefficient operations, disadvantageous shipyard conditions, or both. SE is expressed as technical efficiency (TE) divided by pure technical efficiency (PTE). Efficiency scores produced by the CCR model represent technical efficiency (TE) and are based on the assumption of proportionality between inputs and outputs. Pure technical efficiency (PTE) is represented by efficiency scores produced by the BCC model and take into account that changes in inputs and outputs are not always proportional. If a DMU is efficient in the BCC model but is inefficient in the CCR model, then that DMU is said to be locally efficient but not globally efficient. In other words, the DMU is efficient when you take into account its shipyard conditions but inefficient purely in terms of operations.

Since an improvement in shipyard performance can be realized by either a reduction in inputs while maintaining current output levels or by an increase in output levels while maintaining current input levels, both input and output orientation could be used. However, the objective of this study is to establish best practice shipyards in terms of current operational conditions. Therefore, the input orientation of the DEA model is not appropriate. Hence, output orientation is better suited to establish best practice shipyards given current conditions. The output orientation of the DEA model aims to maximize output given current input levels. Consequently, the external analysis was completed using both an output oriented CCR model and an output-oriented BCC model.

3.4.2.3 - Internal Analysis

The NCFS owns, operates, and maintains a total of 21 ferries, varying in size, geometry, capacity, and utilization. The ferries are categorized into three separate classifications based on vessel size characteristics as well as passenger and vehicle capacity. The ferry classifications are Hatteras Class, River Class, and Sound Class. Hatteras Class ferries have vehicle and passenger capacities of 26 and 149, and are 150 feet in length. River Class ferries are 180 feet in length and have the capacity to hold 38 vehicles and 300 passengers. Sound Class ferries, the final ferry classification, are the largest vessels operated by the NCFS. Ferries in this class are 220 feet in length and have the capability to accommodate up to 50 vehicles and 300 passengers. In terms of gross tonnage, the largest vessels in the Hatteras, River, and Sound Classes are 280 tons, 462 tons, and 867 tons, respectively. Out of the 21 total ferries, eight are Hatteras Class, nine are River class, and four are Sound Class. Despite the differences in size and utilization characteristics, it has been observed through investigation of previously completed maintenance work orders that the types of maintenance and repair activities carried out on ferries and other vessels along with the skilled trades necessary to complete the work are very similar in nature. However, the required maintenance levels and the duration of dry-docking vary considerably from vessel to vessel. These discrepancies are partially the result of differences in physical characteristics such as length, depth, and weight, along with on-board mechanical and electrical systems, vessel utilization and classification. Additionally, age of the vessel under repair, environmental conditions, and the type of work done by the boat also has an effect on the amount of work to be done and maintenance duration.

Per U.S. Coast Guard regulations, these ferries must be dry-docked for repairs and refurbishment twice every five years. Consequently, to meet these requirements, this requires the shipyard to complete 21 dry-docks every two and a half years or every 30 months. In order to meet these requirements the shipyard would have to complete on average one vessel every 1.43 months or every 43 days, which equates to approximately 8.39 vessels per year. Currently, dry-docks times for vessel refurbishment are estimated based on experts opinions. Moreover, the shipyards planned length of refurbishment for each vessel regardless of size or age is 90 days. Through discussion with shipyard personnel, a 60 day dry-dock period would be ideal and a 120 day refurbishment is the worst-case scenario. Despite each refurbishment being planned for 90 days, historical data from the past 18 months shows that most refurbishments are not completed within the scheduled timeframe. Furthermore, there are times when vessels are sent back into service without being fully refurbished as a result of these schedule overruns.

The purpose of the internal analysis is to evaluate the efficiency of Manns Harbor's internal repair operations to identify possible inefficient departments or operations within the organization. In addition to evaluation of internal operations, the internal analysis aims to determine whether the current planned refurbishment times are a realistic and if not determine a more realistic refurbishment schedule based on current operational levels. Data available for internal analysis is inclusive of data pertaining to completed dry-dock refurbishments over an 18-month period from 2015 to 2017. Data was collected directly from the NCDOT's SAP system during a visit to the shipyard. In total, the data is inclusive of nine work orders, eight of which are ferries, and the other being one of the state's crane barges. Of the ferry refurbishments completed, two are Hatteras Class, three are Sound Class, and three are River Class. Because of the available data, the internal analysis can be carried out in more detail than the external analysis. Internal analysis will be carried out in two separate manners, first at the work order level and then at the departmental level per work order. A full list of DMUs available for evaluation can be seen in Table 13.

Table 13: Internal Analysis DMU List

DMU	Ferry Class	Year
DMU 1	Hatteras	2015
DMU 2	Sound	2015
DMU 3	Sound	2016
DMU 4	River	2016
DMU 5	River	2016
DMU 6	Crane Barge	2016
DMU 7	Sound	2017
DMU 8	River	2017
DMU 9	Hatteras	2017

As previously mentioned, there are instances in which ferries are returned to service before full refurbishment of the vessel can take place during the dry-docking period due to various reasons but, more often than not, these instances are the direct result of schedule overruns in the shipyard. Because of this, a significant variance in the amount of work (hours) completed on the vessels can be seen in the work orders. Through observation of the internal data, full ferry refurbishment during the dry dock period generally require upwards of 10,000 man-hours to complete. Moreover, six of the nine internal work orders (DMU 1, DMU 2, DMU 5, DMU 6, DMU 8, and DMU 9) had more than 10,000 hours, while the remaining three work orders (DMU3, DMU 4, and DMU 7) were charged less than 10,000 hours. The significance in this is that the three work orders with less than 10,000 hours represent instances when ferries were not fully refurbished prior to leaving the shipyard and returning to service. Furthermore, DMU 7 was only charged 4,211 hours while dry-docked, while DMU 3 and DMU 4 were charged roughly 7,000 hours each. Because of the inconsistency of hours charged to the internal work orders, the three DMUs that were not fully refurbish can be considered outliers in the data and have the potential to skew the efficiency scores represented by DEA results. In addition, this introduces an added degree of uncertainty into the DEA model because all of the work orders are not full refurbishment projects. However, in the case that these DMUs significantly alter the results of DEA, the analysis can be altered to exclude the DMUs that are not full refurbishments and reassessed. Moreover, with the use of the DEA software package, multiple iterations of the DEA model can be run, and the results of each iteration can be contrasted amongst the others. This will allow the potential effects of the inclusion and exclusion of the DMUs that are not full refurbishments to be realized in the results as well as allow the researchers to present the results and conclusions of the analysis in a more accurate manner.

Input and Output Variables

Similar to the external analysis, variables used as input and output variables for the internal analysis must be inclusive of relevant factors related to production. Nonetheless, because this analysis is inclusive of only Manns Harbor operations, several variables used in the external analysis provide no value for the internal analysis. Namely, shipyard capacity and the qualitative index are not necessary for the internal analysis because all work was completed at the same shipyard. However, number of employees, labor productivity, and refurbishment time all provide value for the internal analysis. Each of these variables remain the same as the external analysis with the only variation being the levels at which they are calculated. Rather than focusing solely on a work order level, number of employees, labor productivity, and refurbishment time will also be calculated at the departmental level per work order. In addition to these variables, a new variable will also be used in the internal analysis performed at the work order level in order to evaluate the feasibility of scheduled refurbishment times. The new variable, schedule delay, will be used to calculate the schedule variance from planned refurbishment times to actual refurbishment times and will represent the gap between planned and actual work. To calculate the schedule delay variable, 90 days will be used as the planned refurbishment time and the schedule delay will be calculated as the actual time (days) required to complete the refurbishment minus the planned 90 days. The actual time for vessel refurbishment used to calculate schedule delay is the duration used in the variable refurbishment time and is calculated the same way as described in the external analysis section. In total, one input and three outputs are used, therefore meeting the discriminatory requirements of DEA. The inputs and outputs used in the internal analysis can be seen in Table 14.

Table 14: Internal Analysis Inputs and Outputs

	Variable Description	Abbreviation	Unit of Measure
Input	Number of Employees	#EMP	-
Outputs	Labor Productivity	PROD	cgt/hr
	Schedule Delay	SDEL	1/days
	Refurbishment Time	RTIME	1/days

DEA Model Selection

To complete the internal analysis both the CCR and BCC models will be utilized. Analogous with the external analysis an exact RTS type cannot be determined for the internal analysis with certainty because exact output patterns and characteristics are not known. Output orientation will be utilized for both models. Output orientation is chosen over an input orientation because the number of employees in each department is related to employment levels of the shipyard, which is relatively uncontrollable by the shipyard, and labor productivity is related to the size of the vessel under repair and the amount of work to be completed with are both uncontrollable by the shipyard. Additionally, evaluating the internal operation through an output-oriented analysis will allow determination of an efficient refurbishment time to be identified. In other words, output-orientation allows efficient operations to be identified based on the existing work conditions in the shipyard. The outputs used in the analysis, labor productivity, schedule delay and refurbishment time all require a reduction to correlate with improved performance. Therefore, the inverse of each must be used in the DEA model.

Internal analysis of Manns Harbor operations will be conducted by two separate DEA assessments. The first assessment will evaluate the internal operations from a holistic standpoint inclusive of all shipyard departments on a per work order basis. Alternatively, the second assessment will evaluate internal operations at an individual departmental level on a per work order basis. More specifically, the first assessment will be conducted in similar fashion to the external analysis to evaluate the efficiency with which the shipyard performed work on each work order. The second assessment method is aimed at evaluating the efficiency with which individual shipyard departments performed work on each work order. Therefore, the DMUs used in the second assessment method will not be the work order as a whole; they will be individual departments per work order (i.e., DMU1-Docking, DMU2-Docking, DMU3-Docking, etc.). Moreover, in the second assessment, the analysis will be carried out for all of the departments employed at the shipyard. In other words, a separate analysis will be carried out for each shipyard maintenance department including docking, hull, piping, machinery, operation activities, electrical, and paint. A visual depiction of the DMUs used in the second assessment can be seen in Table 15. While both assessment methods will use the abovementioned input and output variables, the level at which they are calculated is not the same. In the first assessment, input and output variables will be calculated on a work order basis. Alternatively, the variables will be calculated on a departmental level per work order in the second assessment.

Table 15: Departmental Level DMU Example

	Shipyard Departments***						
	Docking	Hull	Piping	Machinery	OpAc	Electrical	Paint
DMUs *	1126 - Docking	1126 - Hull	1126 - Piping	1126 - Machinery	1126 - OpAc	1126 - Electrical	1126 - Paint
	1227 - Docking	1227 - Hull	1227 - Piping	1227 - Machinery	1227 - OpAc	1227 - Electrical	1227 - Paint
	1157 - Docking	1157 - Hull	1157 - Piping	1157 - Machinery	1157 - OpAc	1157 - Electrical	1157 - Paint
	1158 - Docking	1158 - Hull	1158 - Piping	1158 - Machinery	1158 - OpAc	1158 - Electrical	1158 - Paint
	1215 - Docking	1215 - Hull	1215 - Piping	1215 - Machinery	1215 - OpAc	1215 - Electrical	1215 - Paint
	1861 - Docking	1861 - Hull	1861 - Piping	1861 - Machinery	1861 - OpAc	1861 - Electrical	1861 - Paint
	2140 - Docking	2140 - Hull	2140 - Piping	2140 - Machinery	2140 - OpAc	2140 - Electrical	2140 - Paint
	3137 - Docking	3137 - Hull	3137 - Piping	3137 - Machinery	3137 - OpAc	3137 - Electrical	3137 - Paint
	3138 - Docking	3138 - Hull	3138 - Piping	3138 - Machinery	3138 - OpAc	3138 - Electrical	3138 - Paint

*** Each DMU is identified by the last four digits of the work order and the specific shipyard department**
***** Each shipyard department will be carried out by a separate iteration of DEA**

3.5 - Research Limitations

Below is a list of limiting factors related to the scope of this research and the sources of possible uncertainty:

1. While the objective of this research is to develop a framework for use as a management tool in ship maintenance and repair facilities to assess the productivity and efficiency facility operations, and the steps can be replicated for application at other shipyards, this methodology is specifically tailored for the NCDOT and Manns Harbor Shipyard. As a result, some of the variables identified in this research are based on the characteristics of Manns Harbor Shipyard and the specific targets of this study and therefore, may not apply to other facilities. Moreover, Manns Harbor is a state-owned public shipyard; therefore, the performance benchmarks set forth in this study may not be applicable in the private industry.
2. Due to the recent implementation of the SAP System for Manns Shipyard, historical maintenance data for the shipyard was only available for an 18-month period. Additionally, due to the competitiveness of the ship repair industry and the lack of public ship repair facilities, a limited number of facilities agreed to participate and provide operational data for use in this study. As a result, the efficiency analysis presented in this report is dependent on a very limited data set. Moreover, operational data collected for comparison in this research was provided by facilities operating in the private sector. The comparisons of a public shipyard to private facilities along with the limited data set represent the major sources of uncertainty pertaining to this study.
3. Productivity is difficult to represent in the service industry due to the multitude of factors that can affect productivity. Furthermore, no standard production rates are available for

reference in the ship repair industry. Therefore, no benchmark or baseline production rates were available for comparison to those calculated in this research.

3.6 - Validation of Results

As stressed previously, the main downfalls surrounding the results of DEA are that in many instances they are subjective in nature because DEA is a non-parametric methodology therefore statistical tests are not capable of easily evaluating the validity the results and the results provided by DEA are heavily dependent the accuracy of the data used as input and output variables in the analysis. As a result, validation of the results presented by DEA is often a challenge and understanding that the results are subjective in nature is vital when presenting conclusions drawn from DEA. However, despite the challenges and limitations surrounding the validation of results provided through DEA, to provide objectivity to the DEA results, two separate methods are utilized to provide validation. The first validation method to ensure the accuracy of the DEA results is to perform a sensitivity analysis on the input and output variables utilized in both the internal and external analyses, as well as the efficiency scores provided by the DEA models. The second method of validation is provided by comparison of the results presented in the external analysis with the results of the qualitative analysis of shipyards.

Because DEA results are heavily reliant on the data used as input and output variables, understanding the effects of change or error within the data set is important to ensuring conclusions drawn from the results are credible. Sensitivity analysis is a methodology that allows investigation of these potential changes and errors and their impacts on the conclusions drawn from results (Pannell, 1997). One of the major challenges encountered when analyzing the results of DEA or any other methodology aimed at developing an optimal solution from a set of inputs and outputs is dealing with uncertainty amongst the data set. Uncertainty amongst the data used as inputs and outputs translates into uncertainty in the results produced by the DEA model, therefore making decisions or recommendations from the results is further complicated. However, one of the primary uses of sensitivity analysis is to deal with uncertainty in data. Sensitivity analysis assists decision makers with uncertainty amongst data because the results of the analysis provide information concerning the circumstances in which the optimal solution of DEA would change based on changes to the input and output variables (Pannell, 1997). Therefore, performing sensitivity analysis on the input and output variables used in this study will allow the researchers to identify critical values where the optimal solution (efficiency score) in the DEA model changes. Additionally, sensitivity analysis also allows identification of sensitive or important variables amongst the data set, which allows recommendations provided in this study to be flexible in nature and dependent on a specific set of circumstances. This provides a significant amount of validation to the results of this study because it will allow identification of multiple strategies to improve efficiency within the shipyard while also identifying to what degree specific changes to shipyard operations have an effect on the overall efficiency of the shipyard. In other words, sensitivity analysis of the input and output variables will allow the researchers to identify the most critical variables related to shipyard efficiency and provide recommendations based on what changes will provide the most benefit to shipyard operations. Moreover, sensitivity analysis of the data will allow the researchers to understand the relationship between input and output variables and to determine the robustness of the optimal solution with changes to different inputs and outputs (Pannell, 1997).

In addition to performing sensitivity analysis on the input and output variables, sensitivity analysis will also be performed on the efficiency scores produced by the various iterations of the DEA models. Because DEA is a nonparametric methodology and efficiency scores are measured relative to an optimal production frontier, the results produced by DEA models cannot be easily analyzed by traditional sensitivity analysis methods (Simar & Wilson, 1998). However, initially introduced by Efron (1992), the bootstrap method is a tool developed to analyze the sensitivity of efficiency scores produced in nonparametric models to sampling variations. The basic notion behind the bootstrapping method is based on idea of repeated simulation of the data-generating process and applying the original estimator to each simulated sample so that the resulting estimates of efficiency represent the distribution of the original data sample (Simar & Wilson, 1998). The significance in applying the bootstrap method to DEA is realized when comparing the performance of one shipyard with the performance of another. When comparing the performance of two shipyards solely based on the original scores produced in DEA, the efficiency or performance of one shipyard compared to another can show significant differences in efficiency scores, which represents that one shipyard's performance is much higher than another shipyard. However, often times the difference in technical efficiency or performance of the shipyards is much less dramatic than the original efficiency scores show. This is where the utilization of bootstrapping provides a significant benefit when analyzing results. Applying the bootstrap method, multiple simulations of the data set are performed and the results provided include a bias-estimate, a bias-corrected efficiency estimate, a median of bootstrap estimated efficiency scores, and the standard deviation of the efficiency estimates (Simar & Wilson, 1998). Calculation of these aforementioned results provides a more robust representation of the technical efficiency of the entities under evaluation. Bootstrapping will allow the researchers to compare the performance of shipyards against each other in a more objective manner. More specifically, sensitivity analysis of the efficiency scores will reveal the sensitivity of the original efficiency scores with respect to variations in the original data or in other words, bootstrapping will enable the researchers to more accurately evaluate the efficiency scores produced by the DEA model. Thus, offering increased validation to the results and increased understanding of shipyard performance with regard to variations of inputs and outputs. Furthermore, the PIM-DEA software chosen to perform the analysis has a built-in tool to perform bootstrapping allowing the researchers to perform sensitivity analysis of the efficiency scores in an efficient manner.

Along with sensitivity analysis of inputs and outputs and bootstrapping of DEA efficiency scores, validation of the results provided by DEA external analysis will also be done through comparison with the results of the qualitative analysis. As stated previously, the purpose of the qualitative analysis was to provide a pragmatic evaluation of shipyard operational performance based on the opinions and experts of those performing work in the industry. The benefit provided by comparison of DEA results to the qualitative results is an additional means of validation to the recommendations provided to increase shipyard performance. For instance, if the results provided through DEA show that one shipyard in significantly underperforming when compared to the others, evaluation of the qualitative results for both the underperforming shipyard as well as the high performing shipyard(s) will reveal any significant differences in the technologies used or the management strategies utilized between the shipyards. This offers additional information to the researchers when providing recommendations for increased performance. Furthermore, comparison of the DEA results to the rankings provided through qualitative analysis will enable the researchers to determine if a shipyard underperforming purely based on operational efficiency or if the underperformance is caused by qualitative factors in the shipyard, or both. For example, if a shipyard receives a low efficiency score from DEA and but receives a relatively high ranking from the qualitative analysis it can be concluded that the source low performance in the shipyard is caused chiefly by inefficient shipyard maintenance operations. On the other hand, if a shipyard receives a low DEA efficiency score and receives a low ranking from the qualitative analysis it can be concluded that low performance in the shipyard is caused by both inefficient operations as well as qualitative factors in the shipyard. Additionally, comparison between both qualitative and quantitative results will allow validation of the recommendations provided to increase performance in inefficient shipyards. In particular, if a shipyard is inefficient because of labor productivity, comparison of the technology used in the inefficient shipyard with that of an efficient shipyard may reveal that the inefficient shipyard has low labor productivity when compared to partially because the technology levels in the shipyard are much lower than those of the higher performing shipyard. Thus, allowing the researchers to recommend that an increase in the level of technology used in the shipyard would result in higher operational efficiency.

CHAPTER 4: ANALYSIS OF RESULTS

This section presents the results of the qualitative assessment as well as both the external and internal quantitative assessments achieved by applying the methodology discussed in the Research Methodology chapter. In essence, this section follows the same steps and procedures outlined in the Research Methodology chapter. The results from each part of the described methodology are demonstrated and a discussion as well as a visual representation of the data used to carry out the analyses is presented where applicable.

The first step of the methodology, Data Collection, is not included in this section as it was discussed and the available data was presented in detail earlier in the Research Methodology chapter. As previously mentioned however, when appropriate, the data used in the assessments will be shown in the associated subsection.

4.1 - Qualitative Assessment

As discussed in the methodology, 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. Details of the observations made were discussed in the Facilities Summaries – Qualitative Review. However, from these observations two separate components were developed for use in the qualitative assessment, namely Technology and Management/Manpower Strategies. As shown in Figure 15, 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 in order 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 16.

Table 16: 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 16, Shipyard D received the highest ranking, while Shipyard C received the lowest overall ranking of all shipyards. Moreover, the two shipyards with SYMBA classifications of Medium/Small Shipyards, Manns Harbor and Shipyard C, received the lowest rankings amongst all shipyards. Alternatively, the three shipyards classified as Repair Yards with Drydock Facilities (Major Shipyards) all received higher rankings with Shipyard B and Shipyard D receiving significantly higher overall qualitative scores as compared to the other shipyards.

The higher rankings for Shipyard B and Shipyard D can partially be attributed to size of each entity, the scope of their operations, and the vastness of resources available to both shipyards especially when compared to the Medium/Small Shipyards. In addition to these factors however, Shipyard B and Shipyard D also received much higher rankings due to high levels of implementation (score of three or greater) for the qualitative factors identified by industry experts that are related to overall shipyard performance. Namely, both Shipyard B and Shipyard D received high implementation scores for the Advanced Machinery, Organizational Structure, Planning and Scheduling, Efficiency Strategies, and Outsourced Labor categories. Additionally, Shipyard D received the highest score for the Apprenticeship Program category. On the other hand, the remaining three shipyards, Manns Harbor, Shipyard C, and Shipyard E, received a score of one (little to no implementation) for at least five of the seven categories. Manns Harbor received the highest score for the Computerized Maintenance Management System (CMMS) category, while Shipyard C received its highest score in the Outsourced Labor category. Shipyard E received a score of one for five of the categories but received a score of four for both Apprenticeship Program and Outsourced Labor.

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 External DEA Assessment of quantitative operational data. Based on the results of the External Assessment, results of the qualitative assessment can assist in identifying potential causes of poor performance or inefficiencies in shipyards and potentially aid in providing recommendations to correct these inefficiencies and increase performance. Moreover, if the results presented in the external assessment align with those presented by the qualitative assessment, an added layer of validation would exist providing increased objectivity to the DEA results. A comparison of the results achieved by the qualitative assessment and the results presented in the external quantitative assessment is provided in a later section of this report titled Comparison of Qualitative and Quantitative Results.

As discussed previously, this research also utilizes the information provided in the qualitative assessment to develop a Qualitative Factor variable for use in the external DEA assessment of shipyard operations. 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. As described in the Research Methodology section, pairwise comparison of the qualitative components allows a weight factor to be assigned to each component based on the components relative importance to productivity and efficiency in the ship repair industry. To perform the pairwise comparison, a survey was sent out to industry professionals that asked them to evaluate the level of importance of each qualitative category with respect to shipyard productivity. To evaluate the level of importance of the qualitative factors, an index of one through seven (1 – 7) was utilized with one (1) being least important and seven (7) being most important. A full description of the index can be seen in Table 12 located in the Research Methodology chapter. In total, eight industry professionals responded to the survey. The participants were inclusive of both internal NCDOT employees as well as experts from the external participating shipyards. Table 17 shows a summary of the results provided through the survey. The last column in Table 17 represents the sum the scores provided by the survey for each qualitative category.

Table 17: Qualitative Survey Results

Qualitative Assessment Component	Response 1	Response 2	Response 3	Response 4	Response 5	Response 6	Response 7	Response 8	LINE TOTALS
Technology									
Advanced Machinery	**5**	**7**	**4**	**6**	**6**	**7**	**7**	**5**	**47**
CMMS	**1**	**7**	**5**	**6**	**7**	**4**	**3**	**7**	**40**
Management/Manpower Strategies									
Organizational Structure	**7**	**7**	**7**	**7**	**6**	**7**	**2**	**7**	**50**
Planning and Scheduling	**7**	**7**	**6**	**5**	**6**	**6**	**5**	**7**	**49**
Efficiency Strategies	**6**	**7**	**3**	**4**	**5**	**6**	**7**	**7**	**45**
Apprenticeship Program	**3**	**7**	**2**	**2**	**7**	**7**	**7**	**5**	**40**
Outsourced Labor	**5**	**5**	**1**	**4**	**5**	**4**	**1**	**4**	**29**

Results of the survey show that of all qualitative categories, the industry professionals believe that Organizational Structure (i.e. specialized project manager) is the most important in terms of shipyard productivity with an average response of 6.25. Planning and Scheduling was considered the second most important with an average response of 6.13 and Advanced Machinery represents the third most important qualitative factor with an average response of 5.88, while Efficiency Strategies are considered the fourth most important factor in shipyard productivity with an average response of 5.63. Following these factors, CMMS and Apprenticeship Program both received an average response of 5.00, tying them for fifth most important. Finally, with an average response of 3.63, Outsourced Labor was considered the least important factor in shipyard productivity. Additionally, three of the top four qualitative categories represent Management/Manpower Strategies subcategories. This suggests that productivity in a shipyard is related to and heavily dependent on the management of the organization and their decisions rather than purely labor and operations thus, validating the inclusion of a Qualitative Factor as a variable in the external DEA assessment. In addition to providing insight on the relative importance of these qualitative factors to shipyard productivity, the results of the survey also assist in validating the choice of qualitative categories by the research team. As shown in the survey results, six out of the seven qualitative categories received an average score of 5.00 or higher meaning they are considered strongly important to most important relative to the scoring index used in the survey. Furthermore, the results of the survey advocate that the qualitative categories chosen by the research team accurately represent important qualitative factors related to productivity in the ship repair industry.

To develop relative weights for each qualitative component, the total score for each category was summed for use in the pairwise comparison, shown in the right-most column in Table 13. The pairwise comparison was carried out by comparing the total score for each category to the score of each of the other categories as a means of determining which category has a greater amount of importance or effect on shipyard productivity. The category that receives the higher total score of the two categories under comparison is considered to "win" that comparison. The category that "wins" the comparison is awarded one point while the category that loses the comparison is not awarded any points. In a case where two categories received the same overall score or "tie", each category is awarded one-half a point (0.5). For example, if you compare Advanced Machinery, with a total score of 47, to Outsourced Labor, with a total score of 29, Advanced Machinery would "win" the comparison and be awarded one point. Conversely, if you compare CMMS to Apprenticeship Program, both categories received a score of 40 therefore the comparison results in a "tie" and each category would receive one-half a point. At the conclusion of the pairwise comparison, the category receiving the most points is considered most important to shipyard productivity. In other words, the category with the most points receives the highest weighting factor of all the qualitative categories. In its entirety, the pairwise comparison required a total of 21 individual comparisons. The qualitative components were all assigned an alphabetical identifier as well as a unique color to identify a "win" for that component within the matrix as shown below. In the matrix, a "win" of a comparison is shown by the letter and color of the winning component. The completed pairwise matrix is shown in Table 18.

Table 18: Completed Pairwise Comparison Matrix

Qualitative Component	ID	A	B	C	D	E	F	G
Advanced Machinery	A	-	A	C	D	A	A	A
CMMS	B	-	-	C	D	E	B F	B
Organizational Structure	C	-	-	-	C	C	C	C
Planning and Scheduling	D	-	-	-	-	D	D	D
Efficiency Strategies	E	-	-	-	-	-	E	E
Apprenticeship Program	F	-	-	-	-	-	-	F
Outsourced Labor	G	-	-	-	-	-	-	-

From the pairwise comparison, the category receiving the most points was Organizational Structure with six points. Planning and Scheduling received was the second highest with five points and Advanced Machinery won four comparisons to receive four points. Efficiency Strategies won three comparisons to amass three points, finishing at fourth overall. The categories of CMMS and Apprenticeship program tied for fifth in the pairwise comparison with each component winning one comparison and tying in another to receive one and one-half points apiece. Outsourced Labor did not win a comparison and received zero points as a result. Therefore, it can be said that Organizational Structure is the most important to shipyard productivity based on the pairwise comparison and should receive the highest weighting factor of all categories in the development of the QUAL variable for DEA. Alternatively, Outsourced Labor did not accrue any points from the pairwise comparison and should receive the smallest weighting factor for development of the QUAL variable.

In order to determine weighting factors for each component, a straightforward weighting equation was developed using the results of the pairwise comparison. In the weighting equation, the value of one point received during the pairwise equation was represented by the variable "x". As previously mentioned, 21 individual comparisons were carried out during the pairwise comparison therefore in total there were 21 possible points available. For that reason, one side of the weighting equation was represented by 21*x*. It was decided that the weighting factors would be assigned from a total of 100 percentage points or a value of one (1.00). Thus, the weighting equation would be set to equal 100. As a result, the weighting equation is represented by the expression $100 = 21x$. However, because Outsourced Labor received zero points in the pairwise comparison, using this equation would result in the category receiving a weighting factor of zero. Although marginal at best, the results of the survey show that industry experts believe that Outsourced Labor is a factor that affects shipyard productivity in some capacity. Therefore, it would be disobliging to assign a weighting factor of zero for Outsourced Labor. Subsequently, Outsourced Labor was assigned a weighting factor of one-tenth (1/10) of a percentage point or 0.001 in decimal form, and the remainder of the weighting factors would result from the remaining 99.9 percentage points. Therefore, the final weighting equation is expressed as $99.9 = 21x$. Solving for "x", the value of one point in the pairwise comparison is determined to be equal to 4.7571 percentage points or 0.04751 in decimal form. The weighting factor for each category was determined by the product of points received in the pairwise comparison and the value of "x". The final weight factors assigned to each category are shown in Table 19.

Table 19: Qualitative Component Weighting Factors

	Pairwise Score	Weight Factor
Advanced Machinery	4	0.190
CMMS	1.5	0.071
Organizational Structure	6	0.285
Planning and Scheduling	5	0.238
Efficiency Strategies	3	0.143
Apprenticeship Program	1.5	0.071
Outsourced Labor	0	0.001

To develop the Qualitative Factor (QUAL) input variable for use in the external analysis, the data from the initial qualitative assessment (shown in Table 16) was used in conjunction with the calculated weighting factors (shown in Table 19) established through pairwise comparison. As discussed in the Qualitative Factor section of the Research Methodology chapter, the QUAL variable for each shipyard was calculated first by multiplying the score the shipyard received for each qualitative category by the relative weighting factor for that category and summing the total of the weighted scores for the shipyard. The total weighted score was then multiplied by 1000 to establish the final QUAL variable for each shipyard. The final calculations and results of the Qualitative Factor (QUAL) input variable can be seen in Table 20. It should be noted that Shipyard E is not included in Table 20. As previously discussed, Shipyard E agreed to provide qualitative data and conduct a site visit with the research team, however the shipyard disinclined to offer any operational data for the analysis. Consequently, Shipyard E is not included as a part of the QUAL variable calculation and will not be included in the external DEA assessment of shipyard operations section of this report.

Table 20: Qualitative Factor Input Variable Results

	Weight	MH	SY B	SY C	SY D
Advanced Machinery	0.190	0.190	0.571	0.190	0.761
CMMS	0.071	0.214	0.143	0.071	0.071
Organizational Structure	0.285	0.285	1.142	0.285	1.427
Planning and Scheduling	0.238	0.476	1.189	0.238	0.714
Efficiency Strategies	0.143	0.143	0.571	0.143	0.428
Apprenticeship Program	0.071	0.071	0.071	0.071	0.357
Outsourced Labor	0.001	0.001	0.003	0.003	0.005
	Total	**1.381**	**3.690**	**1.002**	**3.763**
QUAL Variable (Total x 1000) =		**1380.57**	**3689.79**	**1002.00**	**3763.14**

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, Manns Harbor (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 categories' perceived importance to shipyard productivity and efficiency did have an effect on 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 (Table 16). In the qualitative assessment, Shipyard D received a significantly higher score than Shipyard B. Conversely, with the inclusion of the weighting factors, the difference in the QUAL variable calculated for Shipyard B and Shipyard D is much less significant. Likewise, in the qualitative assessment the scores received by Manns Harbor and Shipyard B were separated by only one point, however Manns Harbor received a much higher QUAL variable score than Shipyard B. This is explained by the differences in the importance (weights) of the various qualitative categories.

In essence, 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 Manns Harbor and Shipyard C. Moreover, as such, Shipyard B and Shipyard D should achieve higher operational performance than Manns Harbor and Shipyard C. However, the use of the QUAL variable in the external analysis will account for the differences in these aforementioned indirect production influencers amongst the shipyards. Therefore, the results presented by the external analysis in the next section will embody all factors that affect shipyard performance allowing the causes of inefficiencies to be identified as either purely operational inefficiency or inefficiency caused by disadvantageous shipyard conditions.

4.2 - External Quantitative Assessment

As explained in the Research Methodology chapter of this report, the purpose of the external analysis is to evaluate the overall operational efficiency of the participating shipyards with an ultimate goal of establishing whether the operations of Manns Harbor Shipyard are efficient through means of Data Envelopment Analysis (DEA). The external analysis used a holistic approach to evaluate shipyard performance by including both direct production factors as well as those indirect qualitative factors that affect shipyard performance. As previously mentioned, the data available to carry out the external analysis was limited to the data the participating entities were willing to provide and the results presented in this section only apply to the data used by this research. The following subsections will describe, present, and explain the process of carrying out the external analysis as well as the results achieved through performing the analysis.

4.2.1 - External Analysis Data

The first step required to carry out the external analysis is to establish and refine the available data in order to determine values for the input and output variables used in the analysis.

As stated in the Research Methodology chapter, the decision making units (DMUs) used in the external analysis will be represented by individual work orders for dry-dock repairs from each shipyard. In total 15 DMUs or work orders are included in the external analysis. The full list of DMUs is shown by Table 10 in the Research Methodology chapter. In addition, the external analysis uses three input variables (Shipyard Capacity, Number of Employees, and Qualitative Factor) and two output variables (Labor Productivity and Refurbishment Time) for five production variables total. Detailed description of these variables was presented in the Research Methodology chapter. The 15 DMUs and five input/output variables provide adequate discriminatory power for the DEA model as outlined in the Literature Review chapter.

Prior to performing the DEA Assessment, the values for input and output variables must be determined for all 15 work orders (DMUs). However, the 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 following paragraphs detail the calculation of the aforementioned variables.

As explained in the Research Methodology chapter, 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 21.

Table 21: Maximum Shipyard Capacities

	Maximum Vessel Capacity			
Shipyard	**Gross Tons**	**Length (ft.)**	**Width (ft.)**	**Shipyard Capacity (SYC)**
Manns Harbor (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 external 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: Manns Harbor – 65, Shipyard B – 250, Shipyard C – 25, and Shipyard D – 380.

The final input variable utilized in the external analysis is a Qualitative Factor (QUAL) related to the qualitative characteristics of each shipyard. As discussed previously, 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. The derivation and calculation of the QUAL variable is discussed in detail in the Research Methodology Chapter as well as the previous section of this report. However, in summary, the QUAL variable encompasses the various technological and managerial strategies levels for the shipyards related to shipyard productivity, and combines these scores with weighting factors based on the opinions of experts in the field for the development of a compound factor that represents the qualitative environment for each shipyard. The results of the Qualitative Factor calculation and the final DEA input QUAL values for each shipyard can be seen in Table 20, shown in the qualitative assessment section of this report.

In combination with these aforementioned input variables, the DEA models in the external 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). Mentioned in the Research Methodology chapter, Labor Productivity must take into account 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. Detailed explanation of the CGT measure and its calculation are provided in the Research Methodology chapter, 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 22.

Table 22: Labor Productivity (PROD) Rates

	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 external analysis, Refurbishment Time (RTIME) is utilized to represent the total number of days a vessel was dry-docked for repairs. As explained in the Research Methodology chapter, 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 23.

Table 23: Refurbishment Time (RTIME) per DMU

	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

4.2.2 - External Analysis DEA Results

For the external analysis, DEA was carried out using both the CCR and BCC envelopment models in the output-orientation. Detailed discussion of DEA model selection is provided in the Research Methodology chapter; however, both models were utilized because a definitive determination of the appropriate RTS type was not possible. Additionally, 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. Prior to presentation and discussion of the results achieved by the external analysis, the complete data set utilized to carry out the analysis is presented in Table 24.

Table 24: External Analysis Data Set

	SYC	#EMP	QUAL	PROD	RTIME
DMU - A1	1149	65	1380.57	0.074	6.410
DMU - A2	1149	65	1380.57	0.188	9.434
DMU - A3	1149	65	1380.57	0.322	8.333
DMU - A4	1149	65	1380.57	0.202	9.434
DMU - A5	1149	65	1380.57	0.104	5.128
DMU - A6	1149	65	1380.57	0.106	5.952
DMU - A7	1149	65	1380.57	0.471	12.821
DMU - A8	1149	65	1380.57	0.120	9.346
DMU - A9	1149	65	1380.57	0.060	5.917
DMU - B1	1971	250	3689.79	0.711	45.455
DMU - B2	1971	250	3689.79	0.238	20.833
DMU - B3	1971	250	3689.79	0.642	28.571
DMU - B4	1971	250	3689.79	0.232	21.277
DMU - C1	1000	25	1002.00	0.057	3.846
DMU - D1	2214	380	3763.14	2.024	62.500

The relative efficiency evaluation of the participating shipyards repair operations was carried out using the empirical data shown in Table 24 relating to shipyard performance indicators for 15 separate work orders. Nine work orders were from Shipyard A (Manns Harbor), 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 and the accompanying limitations described in the Research Limitations section of this report, and therefore may not be applicable in all situations. The relative efficiency scores generated by both the CCR and BCC models as well as the accompanying scale efficiencies are presented in Table 25.

Table 25: External Analysis CCR, BCC, and Scale Efficiency Scores

DMU	CCR Score	BCC Score	Scale Efficiency
A1	50.00	50.00	100.00
A2	73.58	73.58	100.00
A3	68.37	68.37	100.00
A4	73.58	73.58	100.00
A5	40.00	40.00	100.00
A6	46.42	46.42	100.00
A7	100.00	100.00	100.00
A8	72.90	72.90	100.00
A9	46.15	46.15	100.00
B1	100.00	100.00	100.00
B2	45.83	45.83	100.00
B3	64.52	64.90	99.42
B4	46.81	46.81	100.00
C1	77.99	100.00	77.99
D1	100.00	100.00	100.00

The results presented in Table 25 show that DMUs A7, B1, and D1 are 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 aforementioned 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, it should be noted that 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.

As discussed in the Research Methodology chapter, to provide validation and in-depth understanding of the results presented by the external DEA evaluation, sensitivity analysis was performed on input and output variables used in the external analysis. Sensitivity analysis of the input and output variables was performed by evaluating the effects of excluding each variable from the DEA model. In other words, multiple iterations of the DEA models were conducted by excluding one variable at a time and examining the effects on the overall efficiency scores. Results of the sensitivity analysis on the input and output variables of the DEA model show that Number of Employees (#EMP) and Refurbishment Time (RTIME) are the most critical variables. Moreover, the results of the sensitivity analysis show that the external DEA models are most sensitive to #EMP and RTIME. Therefore, it is understood that out of all the variables used #EMP and RTIME have the greatest effect on overall efficiency scores. The results of the sensitivity analysis performed on the input and output variables are presented in Table 26. As seen in Table 26, exclusion of either #EMP or RTIME significantly changes the efficiency scores of the DEA models.

Table 26: Sensitivity Analysis of External Analysis Variables

	Original Scores		#EMP Removed		RTIME Removed	
DMU	**CCR Score**	**BCC Score**	**CCR Score**	**BCC Score**	**CCR Score**	**BCC Score**
A1	50.00	50.00	27.96	50.00	15.71	15.71
A2	73.58	73.58	41.14	73.58	39.92	39.92
A3	68.37	68.37	43.36	68.37	68.37	68.37
A4	73.58	73.58	41.14	73.58	42.89	42.89
A5	40.00	40.00	22.36	40.00	22.08	22.08
A6	46.42	46.42	25.96	46.42	22.51	22.51
A7	100.00	100.00	63.43	100.00	100.00	100.00
A8	72.90	72.90	40.76	72.90	25.48	25.48
A9	46.15	46.15	25.81	46.15	12.74	12.74
B1	100.00	100.00	81.69	88.84	50.25	51.41
B2	45.83	45.83	37.44	40.72	16.82	17.21
B3	64.52	64.90	51.35	55.84	45.37	46.42
B4	46.81	46.81	38.24	41.59	16.40	16.77
C1	77.99	100.00	23.11	100.00	31.46	100.00
D1	100.00	100.00	100.00	100.00	100.00	100.00

Although the above results represent the relative efficiencies of all four shipyards, only the efficiency scores of Manns Harbor (Shipyard A) will be discussed in detail, as the ultimate goal of this research is to provide the NCDOT-FD with analytical results to improve Manns Harbor operations and to aid in developing an overall strategic decision-making plan for the shipyard.

Results presented in Table 25 show that of all completed work orders from Manns Harbor 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 Manns Harbor reveals that the efficiency score for DMU A7 shown in the DEA models may be misleading. As discussed in the Internal Analysis section of the Research Methodology, there are times in which ferries are returned to service before the vessel can be fully refurbished. These instances can be caused by various reasons, but the majority of the time it is the direct result of schedule overruns within the shipyard. In the case of DMU A7, the problem with the efficiency score indicated by DEA arises when you begin to investigate the total hours of maintenance completed on the work order as well as the total refurbishment time for the vessel. As shown in Table 22 and Table 23, the total hours and the total refurbishment time for work order A7 are significantly less than the other work orders provided by Manns Harbor. 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. Because of these extreme variations in hours and refurbishment time, the results presented shown by the original DEA models are skewed. Consequently, in an attempt 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 external DEA assessment with the exclusion of DMU A7 are presented in Table 27.

Table 27: External 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

As seen in Table 27, the results of both DEA models as well as scale efficiency are significantly different, especially for Manns Harbor, as compared to the results of the original DEA models. While the removal of DMU A7 did have an effect on the majority of the resulting efficiencies, DMU B1 and DMU D1 both remained best practice units in both models. Likewise, DMU C1 remained relatively efficient in the BCC model but the unit's efficiency score in the CCR model increased. Unlike the original DEA model iterations however, the only Manns Harbor's work order receiving an efficiency score of 100 was DMU A3 in the BCC model. DMU A3's efficiency scores from both models rose considerably with the removal of DMU A7. Moreover, the efficiency scores of all DMUs rose in both models with the exclusion of DMUs B1, B2, B4, C1, and D1. Additionally, the scale efficiencies presented by the DEA models with the exclusion of DMU A7 changed noticeably. In the new models, only four of the units under evaluation received scale efficiency scores of 100 as opposed to 13 units receiving scale efficiency scores in the original models.

When looking specifically at the results of Manns Harbor, 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 Manns Harbor 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 Manns Harbor 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. A look at the scale efficiencies of Manns Harbor reveals that all of the work orders received scale efficiency scores of less than 100. This indicates that the conditions of the shipyard are disadvantageous as compared to the best practice shipyards, which contributes to the inefficiency shown by the results. In other words, the existing conditions within Manns Harbor (i.e. number of employees, shipyard capacity, or qualitative factors) are a contributing factor to the inefficiency.

Of all Manns Harbor 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 Manns Harbor 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 Manns Harbor work orders are 67.10 and 72.67 in the CCR and BCC models respectively. This indicates on average Manns Harbor'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.

Sensitivity analysis of the input and output variables was performed again after DMU A7 was removed from the analysis. However, results of the second sensitivity analysis produced the same results with Number of Employees and Refurbishment Time being identified as the most critical variables; therefore, these results are not shown. In addition to the sensitivity analysis performed on the input and output variables, the bootstrap method of sensitivity analysis was also performed on the efficiency scores produced by DEA. As stated in the Research Methodology chapter, bootstrapping is done by performing multiple simulations of the DEA model with changes to the input and output variables. Bootstrapping takes into account the effects of variations in the data set and their potential effects on overall efficiency scores thus providing an overall better representation of technical efficiency from the DEA model. For this research, bootstrapping was carried out by performing 1,000 iterations of the BCC DEA model with various changes to the input and output variables. Bootstrapping was only performed on the BCC model because this model does not assume proportionality between the inputs and outputs. In other words, the BCC model recognizes that increases to the input variables (existing shipyard conditions) do not always result in proportional increases to the outputs (i.e. increased productivity and reduction in refurbishment time) or vice versa. The results of bootstrapping are shown in Table 28. The results of bootstrapping provide a more robust and in-depth presentation of the efficiency scores with consideration of variations to the data set. As mentioned in the Research Methodology chapter, there are times when the original scores provided by DEA models show large differences in efficiency scores amongst the DMUs and the performance of inefficient DMUs compared to best practice DMUs is significant. The purpose of bootstrapping is to evaluate the DEA model's overall sensitivity to variations in the data set. The results of bootstrapping often times show less dramatic differences in the performance than those of the original model. However, in this instance, the results from bootstrapping show that overall the DEA model used in this analysis is relatively insensitive to variations of the data set. This is represented by the relatively consistent bootstrapped efficiency scores for each DMU, as shown in Table 28, suggesting that the results provided by the original DEA models are an accurate representation of overall performance.

Table 28: External Analysis Bootstrap Results

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
A1	59.78	57.25	57.99	50.83	59.85
A2	87.97	82.48	83.16	75.95	88.17
A3	100.00	100.00	100.00	100.00	100.00
A4	87.97	80.93	81.16	75.95	88.55
A5	47.82	44.19	45.03	35.52	47.98
A6	55.50	52.19	53.08	43.68	55.61
A8	87.15	83.45	84.32	74.31	87.28
A9	55.18	52.91	53.62	46.92	55.24
B1	100.00	100.00	100.00	100.00	100.00
B2	45.83	41.61	43.03	24.58	45.97
B3	65.73	54.69	59.38	31.46	66.15
B4	46.81	42.58	44.06	25.11	46.93
C1	100.00	100.00	100.00	100.00	100.00
D1	100.00	100.00	100.00	100.00	100.00

Overall, the results of the external DEA assessment suggest that on average the maintenance operations at Manns Harbor Shipyard are inefficient compared to the best practice units by the analysis. As stated previously, Manns Harbor'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. Further discussion of these disadvantageous conditions is provided in the successive Comparison of Qualitative and Quantitative Results section of this report. 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 Figure 11 and Figure 12. Work orders from Manns Harbor are shown enclosed by a rectangle in both figures. As shown in both Figure 11 and Figure 12, at current employment levels Manns Harbor shipyard is under performing for both Labor Productivity and Refurbishment Time. In other words, Figure 11 and Figure 12 reveal that Manns Harbor is inefficient because the shipyard should have increased productivity and lower refurbishment times at current employment levels.

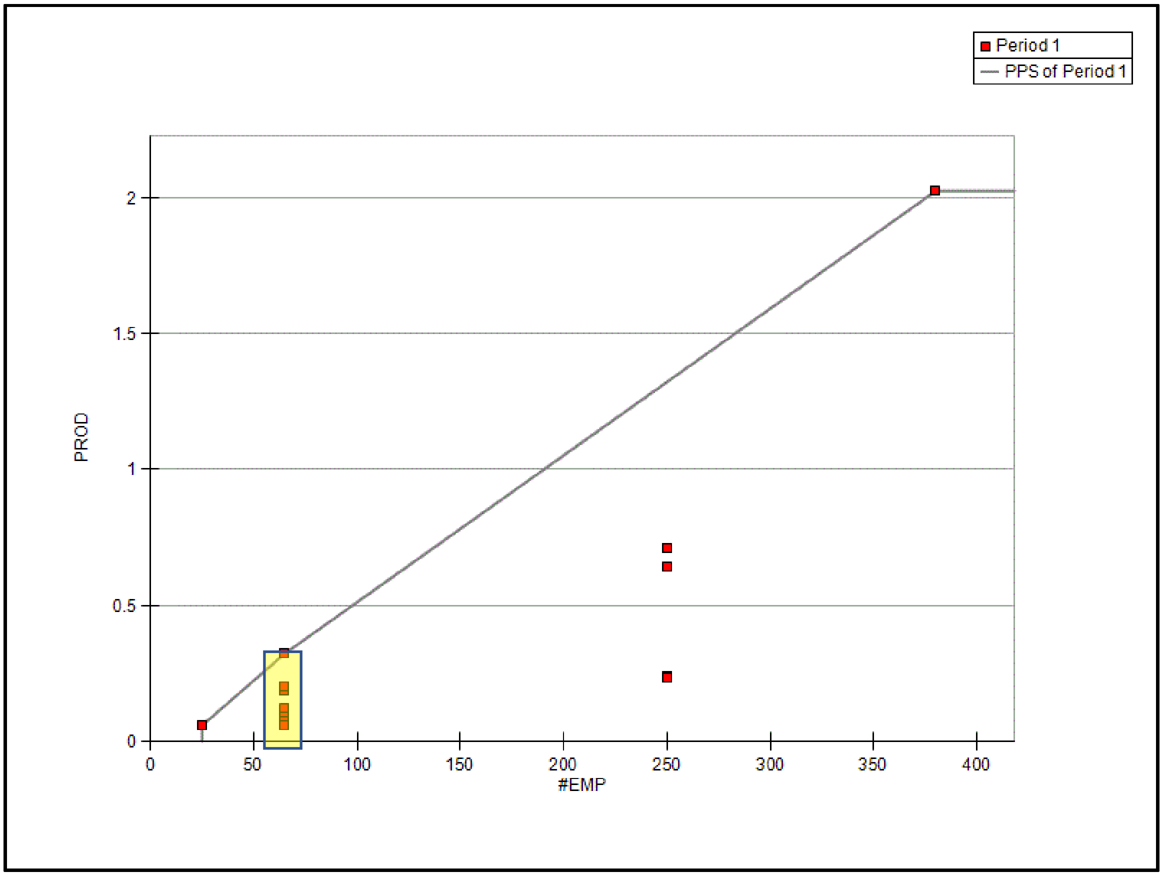

Figure 11: Efficient Frontier - #EMP vs. PROD

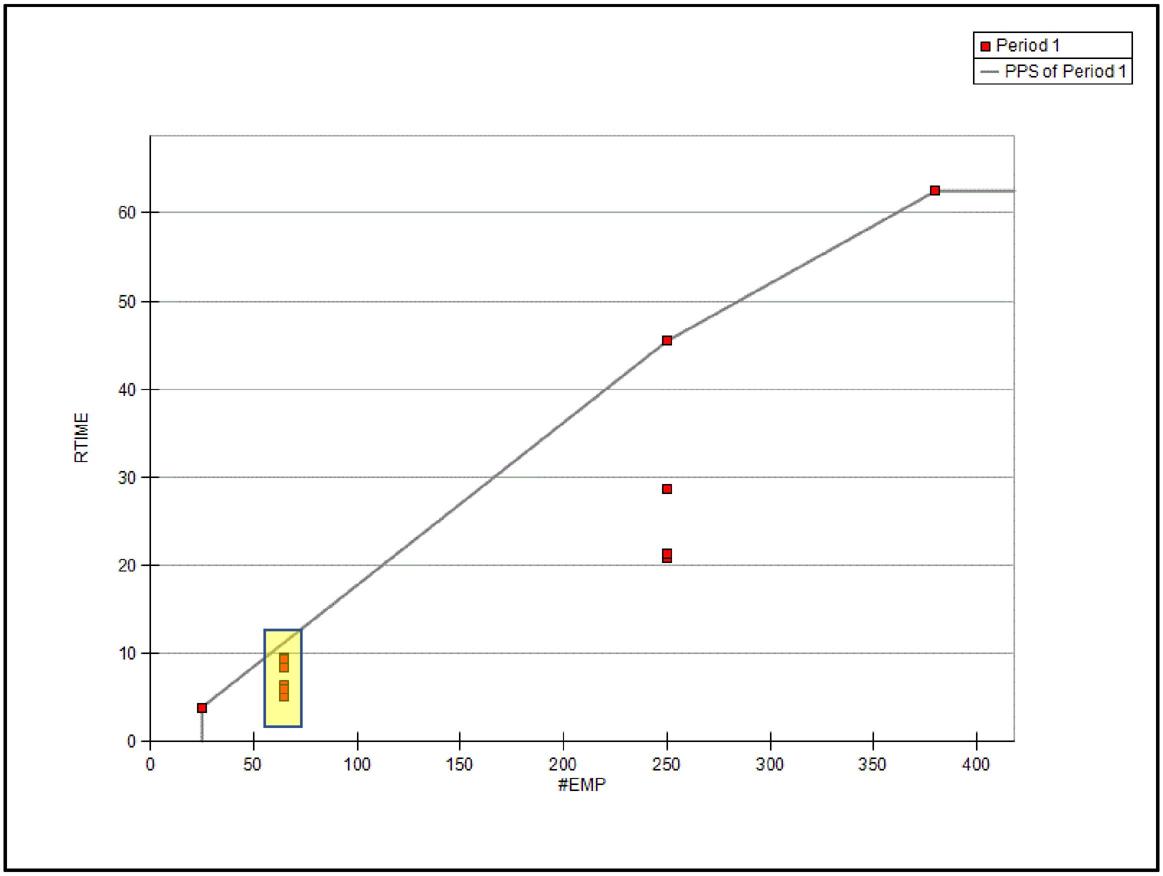

Figure 12: Efficient Frontier - #EMP vs. RTIME

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 Manns Harbor must improve both Labor Productivity as well as Refurbishment Time on their projects. Optimal performance targets for Manns Harbor to become efficient with current shipyard conditions are shown in Table 29. The results shown in Table 29 indicate that Manns Harbor 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, Manns Harbor must achieve a productivity rate of 16.67 hours per gross ton for Hatteras Class Ferries, 12.50 hours per gross ton for Sound Class Ferries, and 14.58 hours per gross ton for River Class Ferries. As shown in Column 4 of Table 29, in some cases this would require improvements to current productivity rates by over 100 percent. However, based on the average productivity rate of all work orders this would require an average improvement to productivity of nearly 39 percent. In addition to improvements to current productivity rates, with current shipyard conditions, Manns Harbor would also have to improve Refurbishment Time on its repair projects. In other words, for the current operations at Manns Harbor to become relatively efficient compared to those best practice units, the overall time it takes to complete dry-dock repairs must be reduced. As shown by the sensitivity analysis results on the DEA input and output variables, Refurbishment Time is a critical factor in the efficiency scores produced by the models. Consequently, it can be said that a reduction in the Refurbishment Times for Manns Harbor projects would significantly improve the efficiency of the work orders. The optimal DEA RTIME target to achieve efficiency is 10.72 or an actual dry-docked time of approximately 94 days. The last column in Table 29 shows the percentage improvement required to achieve the optimal refurbishment time for each work order. From the work orders provided by Manns Harbor, the average time for refurbishment on the vessels with the exclusion of DMU A7 was approximately 141 days. Therefore, to achieve relative efficient operation, based on the average time of refurbishment Manns Harbor would have to reduce the refurbishment time by approximately 33%. In conclusion, the results of the external analysis suggest that Manns Harbor would require significant improvements to productivity and refurbishment time performance in order to become efficient with the work done at best practice shipyards.

Table 29: Performance Targets for Manns Harbor

DMU	PROD Value	PROD Target	PROD Gain (%)	RTIME Value	RTIME Target	RTIME Gain (%)
A1	0.07	0.24	228.01	6.41	10.72	67.29
A2	0.19	0.24	29.11	9.43	10.72	13.67
A3	0.32	0.32	0	8.33	8.33	0
A4	0.2	0.24	20.16	9.43	10.72	13.67
A5	0.1	0.24	133.39	5.13	10.72	109.12
A6	0.11	0.24	128.99	5.95	10.72	80.17
A8	0.12	0.24	102.27	9.35	10.72	14.74
A9	0.06	0.24	304.54	5.92	10.72	81.23

4.3 - Comparison of Qualitative and Quantitative Results

As a means of validating the results attained in the quantitative DEA assessment and investigating the effects of qualitative factors on shipyard performance, a comparison with the qualitative assessment results is necessary. In the qualitative assessment, Shipyard D received the highest score followed by Shipyard B, Manns Harbor, and Shipyard C. Moreover, both Manns Harbor and Shipyard C received significantly lower scores in the qualitative assessment than Shipyard B and Shipyard D. From a theoretical standpoint, this suggests that in terms of technology and management strategies related to shipyard productivity and efficiency Shipyard B and Shipyard D have a significant advantage over Manns Harbor and Shipyard C. In other words, the qualitative conditions at Manns Harbor and Shipyard C put them at a performance disadvantage compared to the other shipyards. Therefore, it was concluded that based on qualitative factors alone, Shipyard B and Shipyard D should perform at a higher level than Manns Harbor or Shipyard C.

The results provided by the external DEA assessment of shipyard operations further validate the conclusions drawn from the quantitative assessment. This can be seen by evaluation of the sources of inefficiency amongst the underperforming units in the external analysis. The two highest performing or best practice DMUs identified in the DEA assessment were DMU B1 and

DMU D1. Only DMU B1 and DMU D1 received relative efficiency in the CCR model results, implying these DMUs were the only efficient units under evaluation in terms of technical operational efficiency. Furthermore, in the BCC model, when shipyard conditions are considered, both Manns Harbor and Shipyard C each had an efficient DMU in the model. Meaning that when the conditions in the shipyard are considered, there were instances where Manns Harbor and Shipyard C operated efficiently. Therefore, when shipyard conditions are excluded neither Manns Harbor nor Shipyard C was determined to be efficient on any work order. However, with the inclusion of their disadvantageous conditions, both Manns Harbor and Shipyard C performed efficiently on one work order. Thus, it can be said that the two shipyards, Shipyard B and Shipyard D, receiving high Qualitative Assessment scores had higher operational performance than Manns Harbor and Shipyard C without the inclusion of the disadvantageous conditions that exist within these shipyards.

Additional validation is provided by the qualitative assessment when analyzing the BCC efficiency and scale efficiency scores presented in the external analysis. Despite displaying high performance by DMU B1, the remaining work orders from Shipyard B were determined to be inefficient in the DEA results. However, analysis of the sources of inefficiency for inefficient work orders provided by Shipyard B validates the conclusions presented in the qualitative assessment. As shown in Table 27, three of the four Shipyard B DMUs received scale efficiency scores of 100 and the remaining DMU received a scale efficiency score of 99.74. As explained previously, this indicates that the cause for the inefficiency for Shipyard B is purely inefficient operations and that the conditions of the shipyard are not disadvantageous. Additionally, it can be seen that Shipyard B and Shipyard D were the only two shipyards receiving scale efficiency scores of 100. More specifically, this indicates that only Shipyard B and Shipyard D did not have existing shipyard conditions that hindered their ability to perform efficiently. The high scale efficiency scores received by Shipyard B and Shipyard D provide validation to the qualitative assessment conclusion that the existing conditions present in both are advantageous in comparison to the two other shipyards.

Alternative to the DEA efficiency results shown for Shipyard B and Shipyard D, neither Manns Harbor nor Shipyard C received efficient scores in the CCR model. However, both shipyards did produce an efficient unit in the BCC model. This suggests that without the inclusion of the disadvantageous conditions shown by the qualitative assessment results both Manns Harbor and Shipyard C are operating inefficiently in comparison to Shipyard B and Shipyard D. This is further supported by the scale efficiency scores received by Manns Harbor and Shipyard C. Outside of DMU A3, which received an efficient score in the BCC model implying that with consideration of shipyard conditions the unit operated efficiently, the remaining work orders provided by Manns Harbor were deemed inefficient by both models. In addition, all Manns Harbor work orders received scale efficiency scores that were less than 100. This indicates that the inefficiency of Manns Harbor Shipyard is caused in part by the disadvantageous conditions that currently exist at the shipyard as well as inefficient operations. Similar to Manns Harbor, Shipyard C was consider efficient only when existing shipyard conditions were considered in the BCC model. Likewise, Shipyard C also received a low scale efficiency score in the DEA results. Unlike Manns Harbor however, Shipyard C's inefficiency can be fully attributed to disadvantageous shipyard conditions.

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 external analysis. Likewise, Shipyard C received the second highest qualitative rank and scale efficiency scores followed by Manns Harbor and Shipyard C in both measures respectively.

Looking at the differences amongst qualitative shipyard factors of the high performing facilities (Shipyard B and Shipyard D) and those of the low performing shipyards (Manns Harbor and Shipyard C) provide insight as to where the possible source of these disadvantages originates. Of the qualitative factors, Manns Harbor and Shipyard C received lower overall scores than both of the high performing shipyards in the following categories: Advanced Machinery, Organizational Structure, Planning and Scheduling, and Efficiency Strategies. As a result, it can be said that Shipyard B and Shipyard D receive their advantageous shipyard conditions from these qualitative categories. The identified qualitative categories in which Manns Harbor and Shipyard C received lower scores than the high performing shipyards correspond with the four most important categories as identified by the industry professional in the survey. Therefore, the conclusion can be made that Manns Harbor and Shipyard C can improve their shipyard conditions and potentially increase their operational performance by making improvements to their technology levels, project management, planning and scheduling techniques, and efficiency strategies utilized.

4.4 - Internal Quantitative Assessment

Discussed extensively in the Research Methodology chapter, the purpose of the internal analysis is to utilize DEA as a means of evaluating the efficiency of internal maintenance operations at Manns Harbor. The internal analysis of Manns Harbor was carried out by two separate DEA assessments. The first DEA assessment was carried out on a holistic work order basis in similar fashion to the External Analysis. The second DEA assessment was carried out at a more detailed, departmental level per work order basis. The purpose of the DEA assessment at the work order basis is to evaluate the efficiency Manns Harbor operations from an overall prospective with the ultimate goal of determining a realistic timeframe for refurbishment projects. Additionally, the DEA assessment at the work order level will assist in determination of whether the current planned maintenance schedule of Manns Harbor is feasible in nature given current shipyard conditions. The purpose of the DEA assessment conducted the departmental level is to evaluate the efficiency of individual work units from work order to work order. The goal of the departmental level assessment is to identify any potential inefficient departments within Manns Harbor so that recommendations for prospective corrective action in those departments can be made.

As mentioned in the Research Limitations section of this report, the data for the internal analysis is limited to the historical data available in the NCDOT's SAP System. At the time of this research, the SAP System had only been implemented for the past 18 months. Therefore, the available data is restricted to nine completed work orders over an 18-month period from 2015 to 2017. These nine work orders are concurrent with the nine work orders utilized in the external analysis for Manns Harbor (DMUs A1-A9) and therefore, are inclusive of the same data. The following subsections of this report will present and discuss the results achieved by the internal analysis carried out at both the work order and departmental levels. Explanation of the data used in the analyses as well as the process of conducting each analysis is also provided within each subsection, where appropriate.

4.4.1 - Internal Analysis Work Order Basis

Similar to the external analysis, the first step in conducting the internal analysis at the work order basis is to determine the values for the input and output variables used in DEA. In total, nine DMUs or work orders are available for conducting the Internal Analysis. As previously mentioned, these are the same work orders utilized in the external analysis for Manns Harbor. Table 13, provided in the Research Methodology chapter, illustrates the full list of DMUs available for the internal analysis and includes the vessel classification and year the work order was completed. Prior to conducting the internal analysis at the work order level, the values for the inputs and outputs must be calculated for each available DMU.

As discussed in the Research Methodology chapter, in total, the internal analysis utilizes four variables as internal shipyard performance indicators. Of these variables, one variable is used as an input variable while the remaining three variables are utilized as outputs in DEA. The lone input variable, Number of Employees (#EMP), is the same variable utilized in the external analysis, however in the internal analysis it is calculated on an individual work order basis. In other words, Number of Employees represents the total number of employees that performed work on each work order. The three output variables utilized in the internal analysis include Labor Productivity (PROD), Refurbishment Time (RTIME), and Schedule Delay (SDEL). Table 14 in the Research Methodology chapter provides a visual summary of the input and output variables employed in the internal analysis. Two of the outputs, PROD and RTIME, are included in the external analysis and remain unchanged for use in the internal analysis at the work order level. Detailed discussion of the calculation of both PROD (Table 22) and RTIME (Table 23) was provided in the external analysis section, therefore additional discussion of these variables is not provided in this section. However, the third output variable, Schedule Delay, is a new variable introduced only in the internal analysis at the work order level. The output variable Schedule Delay was introduced to this analysis as a means of evaluating the feasibility of the current 90 days planned for vessel refurbishment at Manns Harbor. Schedule Delay represents the difference in actual work (time of dry-docked repairs in days) compared to the planned 90 day period. Similar to PROD and RTIME, because Schedule Delay is utilized as an output variable, the inverse of the variable must be used in the DEA assessment. Therefore, Schedule Delay is expressed as the inverse of actual refurbishment time minus the planned 90 days multiplied by 1000 or SDEL = [1/(Actual – 90)] x 1000. The calculation of SDEL for each work order is shown in Table 30. The final data set used to carry out the internal analysis on a work order basis is shown in Table 31.

Table 30: Schedule Delay (SDEL) Calculation per Work Order

DMU	Actual Days	Schedule Delay	SDEL
DMU1	156.00	66.00	15.15
DMU2	106.00	16.00	62.50
DMU3	120.00	30.00	33.33
DMU4	106.00	16.00	62.50
DMU5	195.00	105.00	9.52
DMU6	168.00	78.00	12.82
DMU7	78.00	-12.00	-83.33
DMU8	107.00	17.00	58.82
DMU9	169.00	79.00	12.66

Table 31: Internal Analysis – Work Order Basis Data Set

DMU	#EMP	PROD	SDEL	RTIME
DMU1	61	0.0736	15.152	6.410
DMU2	66	0.1879	62.500	9.434
DMU3	57	0.3219	33.333	8.333
DMU4	58	0.2024	62.500	9.434
DMU5	63	0.1036	9.524	5.128
DMU6	60	0.1059	12.821	5.952
DMU7	55	0.4708	2000.000	12.821
DMU8	64	0.1201	58.824	9.346
DMU9	64	0.0599	12.658	5.917

Like the external analysis, DEA for the internal analysis at the work order level was carried out using both the CCR and BCC models in the output-orientation. Both the CCR and BCC models were used in the internal analysis for the reasons discussed in the Research Methodology chapter. Prior to presentation of the results, further discussion of DMU 7 is required. Discussed in the internal analysis methodology, and further explained in the results of the external analysis, because of various reasons, there are instances at Manns Harbor where vessels are sent back into operation prior to full refurbishment. Moreover, as shown in Table 30, DMU7 is an example of one of these instances. It can be seen that DMU7 was in the shipyard for a significantly less amount of time than the remaining work orders. As discussed in the external analysis, the total hours charged to DMU7 were also significantly less than the remaining work orders. Because of this, as shown by the initial results of the external analysis, the inclusion of DMU7 skews the efficiency scores produced by the DEA models. Therefore, it can be said that DMU7 introduces a bias into the DEA models and provides inaccurate results, which represent a false sense of high performance. As such, DMU7 is excluded from this DEA assessment as well as the DEA assessments carried out at the departmental level in the following section. The exclusion of DMU7 enables the researchers to evaluate Manns Harbor's performance only on complete refurbishments and allows more robust conclusions and recommendations to be made. Despite the exclusion of DMU7, the data used in the internal analysis still provides adequate discriminatory power for the DEA models because the number of DMUs is equal to twice the number of input and output variables.

The relative efficiency scores produced by the DEA models are relative to the empirical data in Table 31 and the associated limitations presented in this research. Therefore, the results presented in this section are relative to this research and does not apply to any other situations. The efficiency scores for the work orders (DMUs) produced by both the CCR and BCC models as well as the scale efficiency of each are shown in Table 32.

Table 32: Internal Analysis - Work Order Basis CCR, BCC, and Scale Efficiency Scores

DMU	CCR Score	BCC Score	Scale Efficiency
DMU1	64.60	67.95	95.08
DMU2	87.88	100.00	87.88
DMU3	100.00	100.00	100.00
DMU4	100.00	100.00	100.00
DMU5	50.04	54.36	92.06
DMU6	60.99	63.09	96.67
DMU8	89.78	99.07	90.63
DMU9	56.84	62.72	90.63

The results presented in Table 32 show that DMU3 and DMU4 are relatively efficient in both the CCR and BCC models. In other words, DMU3 and DMU4 represent "best practice" units and fall on the efficient frontier in for both models. On the other hand, DMU2 is relatively inefficient in the CCR model but relatively efficient in the BCC model. In addition, DMU2 received a scale efficiency score of 87.88, indicating that the source of inefficiency within the CCR model can be attributed to disadvantageous conditions or the inefficiency is related to the Number of Employees utilized to complete the work order. Therefore, it can be said that in terms of pure operational efficiency, Manns Harbor operated efficiently on work orders DMU2, DMU3, and DMU4 or in other words, Manns Harbor operates efficiently on approximately 38 percent of the evaluated work orders. Of these efficient DMUs, two work orders (DMU2 and DMU3) were conducted on Sound Class ferries and the other efficient work order (DMU4) was conducted on a River Class ferry. This indicates that internally, Manns Harbor operates more efficiently on larger ferries than on the smaller ferries in the fleet. This is further validated when looking at the pure operational efficiency (BCC scores) of each ferry classification's work orders. The largest ferries, Sound Class, had an average BCC score of 100. The mid-sized ferries, River Class, had an average pure operational efficiency of 88.48 while, the smallest ferries, Hatteras Class, had an average BCC score of only 65.34. The lone Crane Barge included in the analysis had a pure operational efficiency of only 63.09.

Further investigation of the results presented in Table 32 show that outside of the three aforementioned work orders, none of the remaining work orders received efficiency scores in either model. Furthermore, excluding DMU3 and DMU4, the remaining work orders all received scale efficiency scores of less than 100. Therefore, it can be said that the source of these internal inefficiencies can be attributed to both disadvantageous conditions and pure inefficient operations. In other words, the internal inefficiencies are caused by both the #EMP used on each work order as well as purely operating at less than optimal conditions (i.e. low PROD, high SDEL, and high RTIME). From an overall prospective, looking at the average of all BCC scores it can be said that on average Manns Harbor only operated at 81 percent efficiency over the 18-month period under evaluation.

To investigate the causes of these internal operational inefficiencies further, sensitivity analysis was conducted on the data set used to conduct this iteration of the internal analysis. The result of the sensitivity analysis carried out on the data is shown in Table 33. Because #EMP is the only input variable used in the DEA models it could not be excluded from the DEA model and therefore is not shown in the sensitivity analysis results. From the results of the sensitivity analysis, it can be seen that the exclusion of RTIME had the most significant effect on the efficiency scores of both models. Consequently, it can be concluded that the DEA models are most sensitive to changes in the RTIME variable or in other words, operational efficiency is most affected by RTIME. Though not as significant as RTIME, the exclusion of both PROD and SDEL both had an effect on the efficiency scores produced by the DEA models. As a result, it can be said that the DEA models are less sensitive to changes in PROD and SDEL but very sensitive to changes in RTIME. Therefore, it can be concluded that the main cause of inefficient scores on the internal work orders can be related to extended refurbishment time.

Table 33: Sensitivity Analysis Results - Internal Analysis Work Order Basis

	Original Scores		**PROD Removed**		**SDEL Removed**		**RTIME Removed**	
DMU	**CCR Score**	**BCC Score**	**CCR Score**	**BCC Score**	**CCR Score**	**BCC Score**	**CCR Score**	**BCC Score**
DMU1	64.60	67.95	64.60	64.60	64.60	64.60	28.04	28.04
DMU2	87.88	100.00	87.88	87.88	87.88	87.88	87.88	87.88
DMU3	100.00	100.00	89.88	89.88	100.00	100.00	100.00	100.00
DMU4	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
DMU5	50.04	54.36	50.04	50.04	50.04	50.04	29.22	29.22
DMU6	60.99	63.09	60.99	60.99	60.99	60.99	32.92	32.92
DMU8	89.78	99.07	89.78	89.78	89.78	89.78	85.29	85.29
DMU9	56.84	62.72	56.84	56.84	56.84	56.84	21.96	21.96

In addition to the sensitivity analysis of the output variables, the bootstrapping sensitivity analysis method was applied to the BCC DEA model. Bootstrapping was only performed on the BCC model because it represents pure technical efficiency or, in this research, pure operational efficiency with the assumption that changes to inputs can result in non-proportional changes to outputs. That is, the BCC model accounts for the variations in the number of employees in each work order and accepts that changes to the #EMP variable does not always result in proportionate changes to the outputs. In other words, the BCC model recognizes that an increase to #EMP does not always result in a proportional increase to PROD or decrease to SDEL and RTIME or vice versa. Discussed extensively in previous sections of this report, bootstrapping performs multiple iterations of the DEA model while simulating changes in the original data set to illustrate the effects on the efficiency scores or the sensitivity of the model to changes in the variables. The results of the bootstrapping sensitivity analysis performed on the BCC model are presented in Table 34.

Table 34: Bootstrapping Results – Internal Analysis Work Order Basis

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	67.95	63.83	65.18	50.82	68.10
DMU2	100.00	100.00	100.00	100.00	100.00
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	100.00	100.00	100.00	100.00	100.00
DMU5	54.36	50.63	51.59	40.82	54.51
DMU6	63.09	57.72	59.56	41.28	63.27
DMU8	99.07	98.18	98.13	98.13	99.31
DMU9	62.72	60.62	61.28	54.64	62.79

Overall, the results presented in Table 34 suggest that the DEA model is relatively insensitive to changes in the data set. This is shown by the relatively small differences between the original efficiency scores and the bootstrap mean and median scores. Moreover, this provides confirmation that the original efficiency scores are an accurate representation of each unit's performance. However, it should be noted that the bootstrapped mean and median scores for the inefficient DMUs are lower than the original efficiency scores produced by the model. Furthermore, the original efficiency scores for each inefficient DMU are all bordering on the upper bound of the bootstrapping results. This suggests that the original DEA scores are representative of the best-case scenario for each work order, which shows that the efficiency of each inefficient unit may actually be slightly less than originally indicated. Stated previously, the results of bootstrapping often times show that the variances in performance amongst DMUs are much less significant than displayed by the original efficiency scores. This statement holds mostly true for the results presented in Table 34. For example, the original efficiency scores suggest that DMU6 is more efficient than DMU9. Conversely, the bootstrap mean and median efficiency scores indicate that DMU9 is more efficient than DMU6. On the other hand, the results of bootstrapping also indicate that the difference in efficiency between DMU1 and DMU6 is actually greater than originally suggested. Ultimately, the bootstrapping results show that the results presented in the analysis are indicative of actual performance.

The overall objectives of the internal analysis conducted at the work order basis are to determine if the current planned 90-day refurbishment time for vessels at Manns Harbor is realistic in nature and if the shipyard can meet the current maintenance requirements with the current shipyard operational conditions. In order to investigate these circumstances as well as improve efficiency within the shipyard, the optimal performance targets for efficient operations produced by DEA must be considered. As shown in the sensitivity analysis of the data set, refurbishment time (RTIME) had the most significant effect on efficiency; however, productivity (PROD) and schedule delay (SDEL) each play a role in efficient operations as well. Optimal performance targets for each variable are shown in Table 35. The efficient frontiers shown in

Figure 13, Figure 14, and Figure 15 indicate that performance improvements are required in each of these areas for Manns Harbor to operate efficiently from an internal standpoint.

Table 35: Internal Analysis WO Performance Targets

	PROD			SDEL			RTIME		
DMU	**Value**	**Target**	**Gain (%)**	**Value**	**Target**	**Gain (%)**	**Value**	**Target**	**Gain (%)**
DMU1	0.07	0.20	172.97	15.15	62.50	312.49	6.41	9.43	47.18
DMU2	0.19	0.20	7.45	62.50	62.50	0.00	9.43	9.43	0.00
DMU3	0.32	0.32	0.00	33.33	33.33	0.00	8.33	8.33	0.00
DMU4	0.20	0.20	0.00	62.50	62.50	0.00	9.43	9.43	0.00
DMU5	0.10	0.20	94.23	9.52	62.50	556.24	5.13	9.43	83.97
DMU6	0.11	0.20	90.57	12.82	62.50	387.48	5.95	9.43	58.50
DMU8	0.12	0.20	68.19	58.82	62.50	6.25	9.35	9.43	0.94
DMU9	0.06	0.20	237.23	12.66	62.50	393.76	5.92	9.43	59.44

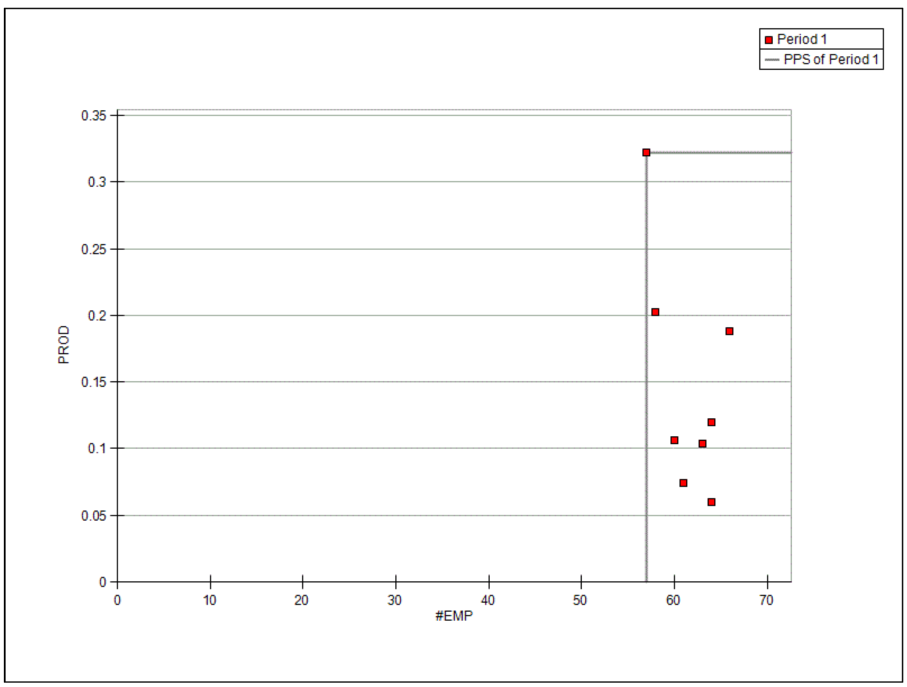

Figure 13: Internal Analysis WO Efficient Frontier - #EMP vs. PROD

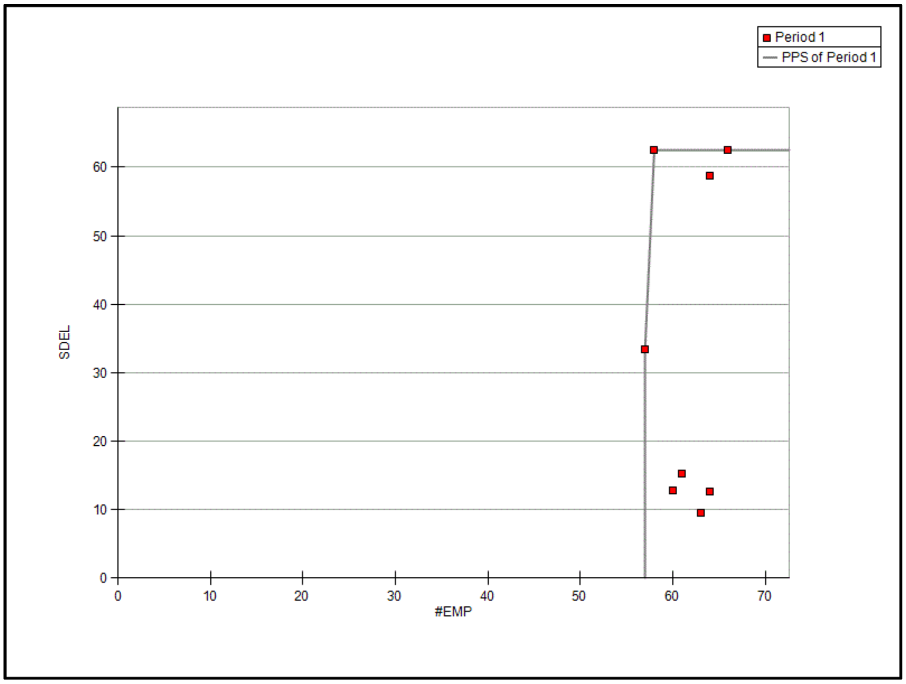

Figure 14: Internal Analysis WO Efficient Frontier - #EMP vs. SDEL

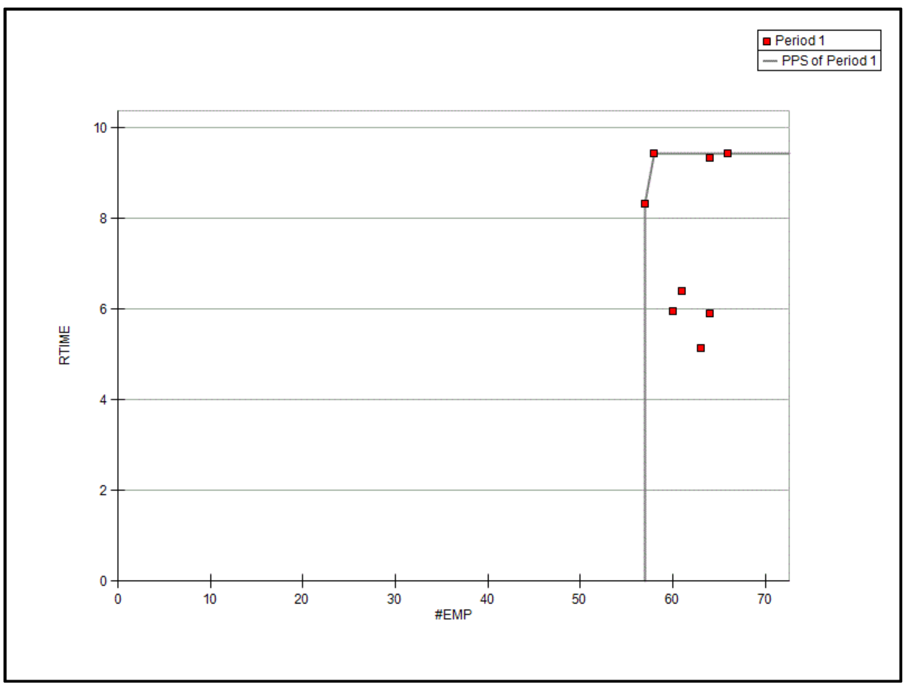

Figure 15: Internal Analysis WO Efficient Frontier - #EMP vs. RTIME

Looking at the results presented in Table 35 as well as Figure 13, Figure 14, and Figure 15 it can be seen that in order to become internally efficient significant performance improvements are required on most work orders for productivity, schedule delay, and refurbishment time. Figure 13 illustrates that in terms of labor productivity (PROD) only DMU3 was identified as a best practice unit. However, regarding the PROD performance targets shown in Table 35 neither DMU3 nor DMU4 require improvement to their productivity rates. This is explained by the scale efficiency scores shown in the model; only DMU3 and DMU 4 received scale efficiency scores of 100. Thus, taking into account the variations in labor used on each work order (#EMP), the productivity level achieved by DMU4 becomes efficient. Alternatively, as illustrated in Figure 14 and Figure 15, DMU2, DMU3, and DMU4 represent best practice units in terms of schedule delay (SDEL) and refurbishment time (RTIME). As a result, these DMUs do not require improvements to SDEL or RTIME as shown in Table 35. As such, all three received efficiency scores of 100 in the BCC model and DMU2's inefficiency in the CCR model can be attributed to low productivity with regard to the labor used on the work order (i.e. disadvantageous conditions or number of employees caused low productivity, as shown by its scale efficiency score of 87.88).

From Table 35 it can be concluded that DMU3 represents best practice internal operations for Manns Harbor. As such, it achieved higher performance for all three outputs as compared to the remaining DMUs. Moreover, DMU3 was the only Manns Harbor work order to receive an efficiency score of 100 in the External Analysis. However, taking into account variances in labor used on each work order, optimal internal performance targets for Manns Harbor to achieve efficiency on the remaining work orders are actually lower than those achieved by DMU3. To become internally efficient, Manns Harbor's performance target for productivity is a DEA PROD value of 0.20 or an actual labor productivity rate of approximately 5.00 hours per compensated gross ton. Converting compensated gross tons back to gross tonnage, Manns Harbor's productivity targets for Hatteras Class ferries, River Class ferries, and Sound Class ferries are 20.00, 17.50, and 15.00 hours per gross ton respectively. The productivity targets identified by the Internal Analysis are very similar to the productivity target identified for Manns Harbor in the External Analysis of 4.16 hours per compensated gross ton. In terms of schedule delay (SDEL), to become internally efficient Manns Harbor's optimal performance target for SDEL is a DEA value of 62.50. This translates to a schedule delay of 16 days. Likewise, Manns Harbor's internal performance target for refurbishment (RTIME) is a DEA value of 9.43 or a total refurbishment time of approximately 106 days. The total of 106 days represents a schedule delay of 16 days from the planned 90 days, which matches the target schedule delay determined through the analysis. Similar to productivity, Manns Harbor's internal performance target for refurbishment time is very close to the 10.72 or 94 days identified in the External Analysis.

Results from both the internal analysis at the work order along with the external analysis, suggest that there are inefficiencies within Manns Harbor in terms of productivity and refurbishment times on their maintenance and repair projects. However, the RTIME performance targets for Manns Harbor to become efficient in either analysis shows that the current planned 90-day refurbishment time is not realistic in nature with the current shipyard conditions. The results of the internal analysis and external analysis suggest that a more realistic time frame for planned refurbishments would be closer to 100 days, if the shipyard could operate with 100 percent efficiency. Furthermore, assuming the shipyard can complete two projects concurrently, the shipyard would only be capable of completing two refurbishment projects every 100 days. This equates to approximately 7.3 vessels per year. As stated in the internal analysis section of the Research Methodology chapter, current maintenance requirements require approximately

8.43 vessels per year to be refurbished. To meet current maintenance requirements with a planned 100-day refurbishment time, the shipyard would have to complete approximately 2.40 vessels every 100 days. Additionally, evaluation of the work orders used in the analysis shows that with the exclusion of DMU7 the average time of refurbishment for each vessel is 140 days. This would require significant improvements to performance by reducing the current average time of refurbishment by nearly 30 percent. With a more realistic 100-day planned refurbishment time with optimal efficiency, it can be concluded that it is fundamentally infeasible to meet the ferry maintenance requirements with the current operating conditions at Manns Harbor.

4.4.2 - Internal Analysis Department Level

Stated numerous times, the objective of the internal analysis carried out at the departmental level is to identify potential inefficient trade departments within Manns Harbor. Identification of any inefficient trade departments will allow the research team to make robust recommendations concerning productivity and efficiency improvements at Manns Harbor. Consequently, unlike the previous sections, the results in this section will be presented in a different manner. Results of the internal analysis at the departmental level will be presented in aggregate. The results of this analysis are presented in aggregate for two primary reasons. The first being that the level or amount of work for each department varies from work order to work order depending a multitude of factors related to the vessel under repair (i.e. age of vessel, vessel condition, etc.). Therefore, establishing performance targets at a departmental level from the analysis is not logical. Secondly, detailed evaluation of individual departments on a per work order basis does not provide value to this research because of the vast amount of uncertainty regarding the variations in quantity of work between work orders. Furthermore, defining optimal performance targets for Manns Harbor departments is not within the scope of this research and therefore will not be investigated.

Similar to the two previous DEA assessments, the first step in conducting the analysis at the departmental level is to refine the available data and establish the values for the input and output variables. The internal analysis at the departmental level utilizes three measures as input and output variables for DEA. Number of Employees (#EMP) is utilized as the lone input variable, while Labor Productivity (PROD) and Refurbishment Time (RTIME) are both utilized as output variables in DEA. Unlike the internal analysis conducted at the work order level, the Schedule Delay (SDEL) variable is not used in this analysis because planned times for execution of work in each department are not known. The input and output variables utilized in the departmental level analysis, #EMP, PROD, and RTIME are the same variables used in both the external analysis and the internal analysis on a work order basis with the same units of measure. Therefore, detailed discussion of the input and outputs are not necessary. The only difference amongst the variables used in the departmental analysis is the level at which they are calculated. Meaning, #EMP is determined by the number of employees per department conducting work on a specific work order and likewise, PROD and RTIME are representative of the productivity rates and refurbishment times of each department per work order. Because of the immense amount of data used in this particular analysis, only the final variables used in DEA are shown in Tables 36 and 37. However, the raw data and detailed calculations of the variables for each department are included in the Appendix of this report.

Table 36: Internal Analysis – Departmental Level Data Set #1

	Docking			Hull			Piping			Machinery		
DMU	#EMP	PROD	RTIME	#EMP	PROD	RTIME	#EMP	PROD	RTIME	#EMP	PROD	RTIME
DMU1	6	8.085	58.824	14	0.710	12.658	5	2.029	33.333	25	0.393	7.092
DMU2	7	12.884	58.824	17	3.959	27.027	5	16.603	83.333	21	0.886	11.905
DMU3	6	14.620	83.333	10	3.801	20.833	3	11.004	40.000	12	9.578	52.632
DMU4	6	7.346	43.478	10	11.073	66.667	7	5.589	43.478	15	4.188	47.619
DMU5	6	5.499	31.250	11	2.987	26.316	4	3.454	30.303	18	0.778	12.346
DMU6	6	6.331	38.462	18	0.567	15.625	8	3.420	33.333	14	1.653	24.390
DMU8	9	8.054	52.632	13	1.016	17.857	5	2.490	31.250	20	1.019	13.889
DMU9	6	6.659	41.667	11	0.713	12.821	7	1.425	16.393	26	0.320	7.246

Table 37: Internal Analysis – Departmental Level Data Set #2

	Operational Activities			Electrical			Paint			Technical		
DMU	#EMP	PROD	RTIME	#EMP	PROD	RTIME	#EMP	PROD	RTIME	#EMP	PROD	RTIME
DMU1	14	1.258	16.393	6	7.509	58.824	32	0.175	9.804	23	0.421	8.772
DMU2	13	3.166	18.868	6	14.323	55.556	38	0.409	9.901	22	1.030	9.804
DMU3	13	4.362	25.000	7	17.240	43.478	27	0.752	10.989	22	1.038	8.475
DMU4	18	2.404	25.000	5	32.761	58.824	33	0.350	15.152	23	1.008	11.905
DMU5	24	0.850	11.494	7	6.385	30.303	31	0.218	5.917	23	0.609	5.988
DMU6	22	1.471	17.544	4	28.777	66.667	29	0.220	7.353	16	0.736	6.452
DMU8	11	2.686	22.727	7	4.524	30.303	33	0.258	10.000	23	0.734	10.101
DMU9	18	0.589	8.621	8	6.261	47.619	32	0.153	6.536	27	0.341	6.410

Tables 36 and 37 show the final input and output variables for each department per work order utilized in carrying out this analysis at the departmental level. For the same reasons mentioned in prior sections of this report, this analysis also excludes DMU7 because of its potential to skew the efficiency scores produced by the DEA models. Like both of the previous quantitative assessments, the internal analysis at the departmental level uses both the CCR and BCC DEA models along with the scale efficiency calculation. Results of the relative efficiency scores achieved by the departmental level Internal Analysis are shown in Tables 38 and 39. Unlike the previous DEA assessments, a sensitivity analysis of the input and output variables used in the departmental evaluation was not conducted. Because the primary purpose of the sensitivity analysis of variables is to identify critical variables that influence efficiency, conducting such an analysis is not necessary in this instance because optimal performance targets at the departmental level are not being identified. Despite the exclusion of the sensitivity analysis on the variables, bootstrapping was applied to the BCC model utilized in this analysis. Bootstrapping was included in this analysis because it analyzes the DEA models sensitivity to changes in the data set and in turn provides a more encompassing representation of departmental efficiency. Results of bootstrapping will be discussed in the following paragraphs, however presentation of the empirical results is provided in the Appendix of this report.

Table 38: Internal Analysis – Departmental Level Results #1

	Docking			**Hull**			**Piping**			**Machinery**		
DMU	**CCR**	**BCC**	**SE**	**CCR**	**BCC**	**SE**	**CCR**	**BCC**	**SE**	**CCR**	**BCC**	**SE**
DMU1	70.59	70.59	100.00	13.56	18.99	71.43	40.00	40.00	100.00	6.47	13.47	48.00
DMU2	75.54	88.13	85.71	23.85	40.54	58.82	100.00	100.00	100.00	12.93	22.62	57.14
DMU3	100.00	100.00	100.00	34.33	34.33	100.00	100.00	100.00	100.00	100.00	100.00	100.00
DMU4	52.17	52.17	100.00	100.00	100.00	100.00	37.27	52.17	71.43	72.38	90.48	80.00
DMU5	37.61	37.61	100.00	35.89	39.47	90.91	45.45	49.14	92.50	15.64	23.46	66.67
DMU6	46.15	46.15	100.00	13.02	23.44	55.56	25.00	40.00	62.50	39.72	46.34	85.71
DMU8	42.11	63.16	66.67	20.60	26.79	76.92	37.50	37.50	100.00	15.83	26.39	60.00
DMU9	50.00	50.00	100.00	17.48	19.23	90.91	14.05	19.67	71.43	6.35	13.77	46.15
Avg. Score	**59.27**	**63.48**	**94.05**	**32.34**	**37.85**	**80.57**	**49.91**	**54.81**	**87.23**	**33.67**	**42.07**	**67.96**

Table 39: Internal Analysis – Departmental Level Results #2

	Operational Activities			**Electrical**			**Paint**			**Technical**		
DMU	**CCR**	**BCC**	**SE**	**CCR**	**BCC**	**SE**	**CCR**	**BCC**	**SE**	**CCR**	**BCC**	**SE**
DMU1	56.67	65.57	86.43	66.67	88.24	58.82	66.73	67.81	98.40	73.68	73.68	100.00
DMU2	74.85	75.47	99.18	66.67	83.33	55.56	59.67	75.29	79.25	100.00	100.00	100.00
DMU3	100.00	100.00	100.00	57.14	65.22	37.27	100.00	100.00	100.00	100.00	100.00	100.00
DMU4	67.22	100.00	67.22	91.08	100.00	91.08	100.00	100.00	100.00	100.00	100.00	100.00
DMU5	23.18	45.98	50.42	57.14	45.45	25.97	43.19	43.54	99.19	57.08	59.30	96.26
DMU6	38.60	70.18	55.00	100.00	100.00	100.00	56.29	59.41	94.74	97.83	100.00	97.83
DMU8	100.00	100.00	100.00	57.14	45.45	25.97	66.50	67.49	98.54	84.85	84.85	100.00
DMU9	23.18	34.48	67.22	50.00	71.43	35.71	44.52	45.21	98.49	45.87	53.84	85.19
Avg. Score	**60.46**	**73.96**	**78.18**	**68.23**	**74.89**	**53.80**	**67.11**	**69.84**	**96.08**	**82.41**	**83.96**	**97.41**

As discussed previously, the intent of this analysis is not to provide specific performance targets at the departmental level but to evaluate the efficiency with which each of the various individual departments within Manns Harbor operate. Therefore, the results achieved by the DEA models shown in Table 38 and Table 39 will be discussed predominantly by the overall average for the department shown in the last row of each table. Prior to in-depth discussion, it should be noted that the results of bootstrapping (shown in the Appendix) imply that the original efficiency scores shown in Tables 38 and 39 are closer to the best-case scenario. This is because the bootstrap mean and median scores for each department are all lower than shown by the original efficiency scores. Moreover, the results of bootstrapping show that the DEA models utilized in the departmental level analysis are quite sensitive to changes in the data set and slight variations to the original values can cause significant changes to the efficiency scores as represented by the upper and lower bounds. As a result, the efficiency scores shown in this analysis are subject to a great deal of uncertainty and therefore are subjective in nature unlike the results of the previous DEA assessments.

Looking at the above results it can be concluded that on average all of Manns Harbor's internal departments operate inefficiently to some degree. However, the sources of inefficiency amongst the departments vary depending on the particular department. For instance, looking solely at the Docking department it can be said that on average the department operates at approximately 63 percent efficiency. Furthermore, the Docking department's average scale efficiency score was 94.05, therefore it can be said that the majority of the department's inefficiency can be attributed primarily to inefficient operations. The same conclusions can be made for the Piping department, the Paint department, and the Technical department because they all received scale efficiency scores of over of 87.00 or above. On the other hand, the Hull, Machinery, Operational Activities, and Electrical departments all received inefficient DEA scores on average as well as scale efficiency scores of 80.57 or less. Thus, the inefficiencies within these departments can be attributed to both inefficient operations as well as disadvantageous conditions (number of employees) that exist within the departments. The Electrical department received the lowest scale efficiency score of all departments at 53.80, indicating that disadvantageous conditions contribute the most to its inefficiency.

Overall, looking at the average pure operational efficiencies (BCC scores) of the internal departments, the Technical department operates at the highest level of efficiency within the shipyard at nearly 84 percent. Both the Electrical department and the Operational Activities department operate at approximately 74 percent efficiency. The Paint, Docking, and Piping departments operate at approximately 70 percent, 64 percent, and 55 percent respectively. The two least efficient internal departments at Manns Harbor are the Machinery department and the Hull department. On average, the Machinery department completes their work with roughly 42 percent efficiency, while the Hull department only completes their work with around 38 percent efficiency. The Machinery department received an average scale efficiency score of 67.96, which indicates disadvantages exist among employment numbers causing the department to be inefficient. The same can be said for the Hull department. However, with an average scale efficiency score of 80.57, the disadvantageous conditions within the Hull department contribute less to the inefficiency than in the Machinery department and as seen by the BCC scores, inefficient operations can be primarily attributed to the Hull departments less than ideal performance.

From the results of the departmental level internal analysis, it can be concluded that inefficiencies within Manns Harbor work orders can be attributed to inefficiencies amongst all of the internal departments. Moreover, it can be said that on all of the work orders under evaluation, two or more individual departments operated inefficiently on all work orders and in some cases, all of the departments operated inefficiently. Therefore, it can be concluded that no single department was responsible for the inefficiencies shown on the work orders in the internal analysis performed on a work order basis. The inefficiencies shown in the analysis at the work order level can be attributed to inefficient operations amidst various combinations of individual shipyard departments. However, it can be concluded that the Hull department and the Machinery department are the least efficient operations at Manns Harbor. As a result, it can be said that significant improvements are required within these departments in order to increase the overall performance of Manns Harbor. Additionally, results show that improvements to conditions within the Hull department and the Machinery department as well as improvements to operations are necessary. In conclusion, the results of this analysis show that while improvements are needed in each individual department, the primary focus of initial improvements at the internal level should be focused specifically toward improving the performance of both the Hull and Machinery departments.

CHAPTER 5: CONCLUSIONS

This chapter is inclusive of an overall assessment of the research project, the results presented by this research, and the recommendations provided to the NCDOT and Manns Harbor shipyard. First, a summary of this this research project and its objectives are presented. Following the research summary, the specific findings of this research are presented and recommendations for improvement at Manns Harbor related to the research objectives are provided. This chapter is concluded by discussing the specific contributions to the body of knowledge provided by this research.

5.1 – Research Summary

Manns Harbor shipyard is the largest state-operated shipyard in the U.S., and is responsible for maintaining the 21 ferries in the NCFS fleet as well as the NCDOT's support vessels. The shipyard self performs all preventative maintenance, emergency maintenance, and scheduled overhauls for all of the above-mentioned vessels. However, in recent years, the shipyard has experienced increased maintenance levels due to augmented ridership, continually aging vessels, and ever-deteriorating channel conditions. These increased maintenance levels in turn affect staffing needs, maintenance scheduling, and resource requirements in the shipyard. Despite the increase to maintenance levels, the shipyard has experienced a decrease in staffing levels.

Maintaining these assets is a critical factor to ensuring these services are provided to the millions of passengers on the state's east coast. Currently, all estimates for vessel refurbishment are based on the opinion of experts within the shipyard. All refurbishments are currently planned for 90 days regardless of vessel type, size, or age. However, with current employment levels and operating conditions, the shipyard is experiencing delays and frequent schedule overruns. The purpose of this research is to utilize DEA as a means of evaluating the current productivity and efficiency of the shipyard with an overall objective of developing methodology that can be used by the NCDOT as a tool for benchmarking and forecasting, as well as strategic, operational, and tactical planning. Specifically, this research attempts to answer the following research questions:

1. Is Manns Harbor shipyard efficient or inefficient compared to other ship repair facilities?
2. Is the current refurbishment time of 90 days realistic in nature? If not, what is a more realistic timeframe and why?
3. Can Manns Harbor meet the required maintenance levels given the number of vessels and the twice per five-year drydocking requirement?

In addition to answering the aforementioned research questions, this research also aims to provide performance targets or benchmarks to the shipyard for efficient operation. To do so, this research utilizes the results provided through DEA in conjunction with the results of a pragmatic qualitative assessment of various shipyard operations in an effort to provide specific recommendations for performance improvement at Manns Harbor. The Qualitative Assessment of the participating shipyards was also used to provide a validation and objectivity to the efficiency scores resulting from the DEA evaluation of shipyard operations and to identify important factors related to productivity and efficiency in shipyards as identified by industry experts. The formal process and methodology for execution of this research is detailed in Chapter 3 titled Research Methodology.

From an overall perspective, this research utilizes the combination of DEA, from an internal and external prospective, and a qualitative analysis of relevant shipyard factors to analyze the current operations at Manns Harbor shipyard. The combination of these assessments provides in-depth insight into these operations by including both direct and indirect factors related to productivity and efficiency within these facilities. The investigation of these qualitative factors not directly related to the production process and acknowledgement of their potential effects on productivity and efficiency is a critical factor in accurately assessing Manns Harbor operations as well as providing robust conclusions and recommendations from the findings of this research. As such, the following section summarizes the findings of applying the research framework outlined in Chapter 3 to the real operational data collected from shipyards and details the associated recommendations for performance improvement at Manns Harbor.

5.2 – Research Findings and Recommendations

As discussed in the prior section, after development of a replicable framework for assessing productivity and efficiency in ship maintenance and repair facilities, the framework was applied to the real data collected from Manns Harbor and the additional three participating shipyards. The framework of this research was divided in to three separate assessments (as delineated in Chapter 3), the qualitative assessment of participating shipyards, the external DEA assessment, and the internal DEA assessment. The individual results from each of these assessments were presented and considered in detail in the previous chapter of this report. Therefore, the successive paragraphs of this section are intended to summarize the findings of each assessment and the implications to Manns Harbor shipyard including recommendations for potential action to improve performance at the facility.

The results of the qualitative assessment indicate that Manns Harbor, in comparison to other shipyards participating in this study, rank relatively low in terms of qualitative factors that influence operational productivity and efficiency. Specifically, Manns Harbor received the second worst overall score out of the five shipyards evaluated. In total, Manns Harbor only received 10 points out of a possible 40 points in the assessment, whereas the two highest scoring shipyards Shipyard D and Shipyard B received 26 and 22 points, respectively. The significant difference in scores received by Manns Harbor compared to those of the best two shipyards can partially be attributed to the variation in size of the entities, the scope of operations, and resource availability amongst the shipyards. However, Manns Harbor's low qualitative score also indicates that the current technology levels and management strategies at the shipyard are inferior compared to other ship repair facilities. In the survey sent out to industry professionals, organizational structure, planning and scheduling, advanced machinery, and efficiency strategies were identified as being the four most important qualitative factors that affect shipyard productivity and efficiency. Consequently, Manns Harbor received low scores in each of these qualitative categories. Likewise, the high scoring shipyards both received high scores for these categories implying that the major qualitative differences between these shipyards can be attributed to these factors. Therefore, in order to achieve conditions nearer to those attained by the top two facilities, Manns Harbor must improve in each of these categories. Additionally, it can be concluded the existing qualitative conditions at Manns Harbor have an effect on the operational performance of the shipyard. Further discussion of the effect of these conditions on performance is provided later in this section.

Comparing the existing conditions of Manns Harbor to those of Shipyard B and Shipyard D reveals the specific areas in which recommendations for improvement related to qualitative factors affecting shipyard performance can be made. In terms of organizational structure, with reference to Section 3.1 and the organizational charts shown by Figure 3a, Figure 3b, and Figure 3d, the most significant difference recognized is that both Shipyard B and Shipyard D both utilize specialized project managers within their organizations and Manns Harbor does not. Both Shipyard B and Shipyard D expressed the importance of utilizing to project managers to track progress and maintain schedule on their projects and allowing the superintendents to focus on overseeing field operations. Alternatively, at Manns Harbor the shipyard superintendent is responsible for project management activities as well as oversight of field operations. There is also a noticeable difference in planning and scheduling between Manns Harbor and Shipyard B. Unlike Manns Harbor, Shipyard B has detailed formal procedures in place regarding planning, estimating, and scheduling based on the quantity of work to be done in both time and materials. However, the main difference between Manns Harbor and Shipyard B with regard to planning and scheduling is that at direct line of communication (i.e. the project manager) exists between management and field personnel to ensure the schedule is maintained. Furthermore, Shipyard B and Shipyard D both use advanced technologies within their shipyard for the purpose of increasing productivity and efficiency. Shipyard B utilizes a robotic-paint blasting method for preparation and paint removal, which is significantly faster than the manual method used at Manns Harbor. Shipyard D utilizes both a plasma cutter and water-jet cutting machine for preparing metal for hull repair and producing small parts, and because of these machines are automated the shipyard has seen improvements to labor productivity. Lastly, in contrast to Manns Harbor, both Shipyard B and Shipyard D have specific efficiency strategies in place within their organizations. Shipyard B utilizes a lean operational strategy, while Shipyard D focuses on on-time delivery and offers employees bonuses for early completion. Nonetheless, it can be said that the addition of a project management role, changes to planning and scheduling procedures, implementation of newer technologies, and employment of efficiency strategies has the potential to provide significant benefits and improvements to Manns Harbor.

Following the qualitative assessment, the first DEA iteration was conducted in the external analysis. The goal of the external analysis was to compare the operations of Manns Harbor with other facilities in order to answer the first research question posed in the previous section. The results of the external analysis indicated that overall, Manns Harbor was inefficient on seven out of eight work orders in comparison to the work orders of the other shipyards. Based purely on operational efficiency, the results indicated that on average Manns Harbor only operates at approximately 73 percent efficiency with regard to the best practice operations. Similar to the results of the qualitative assessment, both Shipyard B and Shipyard D represented best practice units in the external analysis of shipyard operations by receiving efficiencies of 100 in both the CCR and BCC models. Evaluation of the efficiency scores from Manns Harbor showed that the shipyard's inefficiencies were caused by both inefficient operations and disadvantageous shipyard conditions. Additionally, it should be noted that while Shipyard B did achieve a best practice unit, three of its four work orders were determined to be inefficient in both the CCR and BCC models. However, unlike Manns Harbor, Shipyard B's inefficiency was only caused by inefficient operations as indicated by the scale efficiency scores it received. Additionally, Shipyard B and Shipyard D were the only two shipyards to receive scale efficiency scores of 100, indicating that the existing conditions within the shipyard do not hinder their performance; which matches the results in the qualitative analysis that indicated these shipyards have higher levels of technology and management strategies. Because the DEA models used in this analysis were output-oriented, disadvantageous conditions shown in the efficiency scores are related to the inputs used in the analysis. Therefore, because the qualitative characteristics of the shipyards were used as an input variable to DEA, it can be concluded that the existing qualitative conditions within Manns Harbor discussed previously have a negative effect on the shipyards operational performance. This further indicates that improvements need to be made in these areas. Additionally, sensitivity analysis indicated that the employment level of shipyards has a significant effect on efficiency scores in the DEA models. Thus, it must also be noted that employment levels at Manns Harbor potentially play a role in the disadvantageous conditions observed for Manns

Harbor, as well. However, because outsourced labor employment was not included in this analysis due to unavailability of data from the shipyards, recommendations to changes in employment levels at Manns Harbor cannot be made with accuracy. To understand the effects of changes to employment levels, further investigation into Manns Harbor operations would be required.

In addition to disadvantageous conditions, Manns Harbor’s inefficiency in the external analysis also results from inefficient operation as shown by the inefficiency in the BCC model. Manns Harbor’s inefficient operations can be attributed to both low labor productivity and extended refurbishment times as indicated by the results of the analysis. As stated numerous times, one major benefit of DEA is that the methodology allows performance benchmarks or targets to be identified for efficient operations. As a result, optimal targets for labor productivity and refurbishment times were established in order for Manns Harbor to operate efficiently in comparison to the other facilities. The results of the external analysis indicated that Manns Harbor’s performance targets for labor productivity and refurbishment time were 4.17 hours per compensated gross ton and 94 days respectively. More specifically, Manns Harbor would have to achieve labor productivity rates of 16.67 hours per ton for Hatteras Class ferries, 14.58 hours per ton for River Class ferries, and 12.50 hours per ton for Sound Class ferries in order to be operationally efficient in comparison to the best practice shipyards. On average, this would require the Manns Harbor to reduce its current labor productivity rate by nearly 40 percent. Likewise, with an average refurbishment time of 141 days, to achieve operational efficiency in comparison to the other shipyards, Manns Harbor would have to reduce current time by nearly 33 percent. Improvements of this magnitude would require significant changes to current shipyard conditions and operational processes. For these reasons, it can be concluded that Manns

Harbor is inefficient compared to other ship repair facilities because of current shipyard conditions and less than optimal operations. In other words, to operate efficiently in comparison to other facilities, Manns Harbor would have to make significant changes to the shipyard conditions (i.e. qualitative conditions, employment level) while also reducing the hours and days required to refurbish a vessel.

The final step in this methodology involved a second DEA assessment of the internal operations of Manns Harbor. The objectives of the internal analysis were to evaluate internal operational efficiency and to identify any potential inefficient departments within Manns Harbor. Moreover, the results of the internal analysis combined with the results of the external analysis were utilized to answer the remaining two research questions. The internal analysis of Manns Harbor was first conducted at the work order level. The results of this iteration of DEA indicated, from a purely operational standpoint (BCC score), Manns Harbor was internally efficient on three of the eight work orders under evaluation. This indicates that over an 18-month period Manns Harbor only completed approximately 38 percent of the work orders with internal efficiency and the remaining refurbishments were completed inefficiently. Additionally, only two of the internal work orders received scale efficiency scores of 100, indicating that inefficiency on the remaining work orders can be partially attributed to disadvantageous conditions. From an internal standpoint, this indicates that the variation in the number of employees utilized to complete work orders caused inefficiency. In other words, the work order receiving scale efficiency scores of less than 100 achieved lower performance despite using additional resources.

Further analysis of the internal analysis results reveals that Manns Harbor performs most efficiently on the larger Sound Class ferries than on the smaller Hatteras Class ferries. Further proof of this is provided when looking only at the average times of refurbishment for the respective classes. Despite being the smallest vessels, Hatteras Class average refurbishment time was the highest of all classes and the largest Sound Class ferries was the least. On average, Manns Harbor completed work on Hatteras Class ferries with only 65 percent efficiency. Outside of the three internal work orders that received pure operational efficiency scores (BCC scores) of 100, the inefficiency in the remaining work orders can be attributed to inefficient operations with regard to labor productivity, refurbishment time, and schedule delay. To further investigate the causes of these inefficient internal operations the DEA was performed a second time at the departmental level. The results of the departmental level analysis revealed that on average all of the internal departments at Manns Harbor operated inefficiently to some degree. However, the results indicated that out of all internal departments the Hull Department and the Machinery Department operate with the lowest efficiencies. Looking at the average of all work orders, the Hull Department operates with only 38 percent efficiency while the Machinery Department operates with roughly 42 percent efficiency. This suggests that any initial improvements within Manns Harbor should be directed towards these departments because of their low efficiency. Likewise, it is worth noting that the advanced machinery implemented by the other shipyards to increase productivity is directly related to the work performed by these departments.

Like the external analysis, the results of the internal analysis were used to determine performance benchmarks for Manns Harbor's internal operations. The results of the internal analysis established performance targets for efficient internal operation as a labor productivity rate of 5.00 hours per compensated gross ton and a refurbishment time of approximately 106 days. The performance target for refurbishment time was further validated by the 16-day target established for schedule delay. The internal target for labor productivity translates to a labor productivity of 20.00 hours per ton for Hatteras Class ferries, 17.50 hours per ton for River Class ferries, and 15.00 hours per ton for Sound Classes ferries. The values determined for internal performance targets for labor productivity and refurbishment time were very close to those identified by the external analysis.

Analysis of the performance targets for operational efficiency at Manns Harbor identified by both the internal and external analysis results indicate that with current shipyard conditions the current planned 90-day refurbishment time is not realistic in nature even under the best circumstances. If the shipyard operated efficiently with current conditions, the external analysis suggests that a more realistic time for planned refurbishment would be 94 days, while the internal analysis suggest a refurbishment time of 106 days equating to an average of 100 days overall. However, these refurbishment times assume that the shipyard is operating with 100 percent efficiency at the benchmark labor productivity rates further suggesting that the 90-day planned refurbishment time is an unrealistic goal. Assuming the shipyard could operate with 80 percent efficiency on average, a realistic goal for planned refurbishment time would be closer to 120 days, which is still approximately 20 days less than the average time of refurbishment over the 18-month period evaluated.

Moreover, as stated in Chapter 3, current Coast Guard regulations require that each ferry be dry-docked for repairs at minimum twice every five years. Accordingly with the 21 total ferries, on average, to meet this requirement Manns Harbor would have to complete one dry-dock per 43 days or approximately 8.4 vessels per year. Assuming the shipyard can accommodate two projects at once, with full efficiency, and a planned refurbishment time of 100 days, this would only equate to roughly 7.3 completed dry-docks per year, meaning the shipyard would be approximately one vessel per year short of meeting the requirement. At a 100-day refurbishment time, the shipyard would have to complete nearly 2.5 dry-docks per 100 days to meet the requirements. Furthermore, assuming 80 percent average operational efficiency, a 120-day planned refurbishment time, and two concurrent projects, the shipyard would only be able to complete roughly 6.00 dry-docks per year. To meet the maintenance requirements at a 120-day refurbishment time, the shipyard would have to complete on average 2.8 vessels every 120 days. Therefore, from both the internal analysis and external analysis results that with current operating conditions, operating at 100 percent efficiency, Manns Harbor cannot accommodate the current maintenance levels.

Overall the results of presented by both iterations of DEA, suggest that current operations at Manns Harbor are inefficient. The inefficiency found within Manns Harbor can be attributed to existing conditions in the shipyard as well as inefficient processes related to performing refurbishment of vessels. Likewise, potential causes of these inefficiencies were identified and recommendations for potential means of improving performance were provided. Additionally, performance targets were established for Manns Harbor to achieve efficiency at both the internal and external levels. In addition to providing benchmarks for operational efficiency, these targets can also be used in future project planning and tracking to serve as early warning signs of low performance at Manns Harbor. As such, the framework outlined by this research can be used as an analytical tool to assist future planning for the NCDOT and Manns Harbor.

Lastly, all of the results, findings, and recommendations presented in this research are based on the results of the DEA models used and the qualitative information gathered concerning the participating shipyards. While the various benefits of utilizing DEA models were discussed, it is imperative to realize that results of DEA are heavily dependent on the data set used and variables defined in the methodology, therefore the results are relative in nature. As a result, it is essential to understand that the information in this report be understood and treated as such, and not taken as definite conclusions. In spite of the findings of this research, officials concerned with performance improvements and future planning at Manns Harbor should investigate current operations as well as the operations of other similar facilities in depth prior to making any absolute conclusions.

5.3 – Contributions to the Body of Knowledge

In recent history, DEA has been applied to evaluate the efficiency of many various industries both public and private. However, very few pieces of literature focus on the maritime industry or specifically on the ship maintenance and repair industry. Given the significance of this topic to the NCDOT as well as other private entities, improvements in the industry are vital for long-term success and competitiveness of all businesses conducting this type of work. Evaluating the performance of shipyards from a holistic approach provides invaluable information related to organizational improvement. This research provides a foundation for future studies related to performance improvement in the ship repair industry. As discussed in the research limitations there are a limited number of private shipyards that exist in the United States. Therefore, the opportunity exists for future research to improve upon this foundation and further evaluate the ship repair and maintenance industry at the public level.

The methodology and framework outlined in this could be implemented by other state transportation agencies as well as private ship repair entities as a mean of evaluating current performance and establishing benchmarks for future planning and continual improvement. However, it is important to note that the performance variables identified in this research were tailored specifically for the NCDOT and the scope of this research. Replication of this study for other entities for similar objectives should be done with caution and performance indicators must be defined specifically for the conditions and desired outcomes of that entity.

Lastly, an additional important outcome of this study is an overall improvement to the efficiency of North Carolina's state shipyard and ferry operations as a whole. The findings of this research will assist in concentrating the efforts required to improve the performance of Manns Harbor resulting in more effective and efficient utilization of resources for the NCDOT. Thus, leading to potential cost and time savings for the state, all while providing enhanced services to the millions of passengers annually who utilize the services provided by the NCFS.

5.4 – Significant Contributions to the NCDOT

The following list is provided as a summary of the key findings and recommendations found by this research as they pertain to Manns Harbor and the NCDOT operations.

- Overall, Manns Harbor is inefficient compared to other shipyards performing similar types of work. The inefficiency of Manns Harbor can be attributed to inferior technology levels and management strategies, as well as inefficient maintenance and repair operations.
- The current planned 90-day refurbishment time at Manns Harbor is unrealistic in nature with consideration of current shipyard and operational conditions. Based on the results of the research, a more realistic timeframe for planned refurbishment would be nearer to 120 days.
- At current operational levels, the results of the research indicate that Manns Harbor cannot currently meet the dry-docking requirements set forth by the US Coast Guard. Therefore, this implies that Manns Harbor cannot meet the current maintenance schedule requirements for the ferry fleet.
- From an internal operational standpoint, the Hull and Machinery departments operate at the least efficiency of all Manns Harbor departments and contribute the

most to the inefficiency of the shipyard. However, results show that a minimum of two departments operate inefficiently on each work order examined over the 18-month period.

- From both an internal and external perspective, the main causes of Manns Harbors low operational efficiency is due to low labor productivity and extended refurbishment times. On average, to operate efficiently, Manns Harbor would have reduce the total hours and time of refurbishment on work orders by approximately 30%.
- Based on the results of the research along with investigation of qualitative factors related to productivity and efficiency in high performing ship repair facilities, the following list provides potential recommendations for improvement in the overall efficiency and performance of Manns Harbor:
    1. Improvements to technology levels in the Hull and Machinery departments aimed at reducing the amount of manual labor required to carry out the tasks associated with these departments.
    2. Changes to management strategies and organizational structure of the shipyard including:
        - Implementation of a Project Management/Project Manager role
        - Development of formal planning and scheduling procedures
        - Development and employment of strategies aimed to increase the performance within the shipyard such as changes to work processes and/or incentives for employees to complete projects early.

3. In-depth analysis of current staffing levels to evaluate the potential for improvements associated with increasing employment in the shipyard and/or utilization of outsourcing in conjunction with in-house labor to complete refurbishment projects in a more efficient manner.

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APPENDIX: INTERNAL ANALYSIS – DEPARTMENTAL LEVEL DATA AND CALCULATIONS

Table A1: Number of Employees per Department

	Docking	Hull	Piping	Machinery	OpAc	Electrical	Paint	Technical
DMU1	6	14	5	25	14	6	32	23
DMU2	7	17	5	21	13	6	38	22
DMU3	6	10	3	12	13	7	27	22
DMU4	6	10	7	15	18	5	33	23
DMU5	6	11	4	18	24	7	31	23
DMU6	6	18	8	14	22	4	29	16
DMU8	9	13	5	20	11	7	33	23
DMU9	6	11	7	26	18	8	32	27

Table A2: Total Hours per Department

	Docking	Hull	Piping	Machinery	OpAc	Electrical	Paint	Technical
DMU1	124	1411.9	494	2553.8	796.6	133.5	5724.75	2379.2
DMU2	174.1	566.5	135.1	2530.6	708.4	156.6	5488.5	2177.7
DMU3	141.5	544.3	188	216	474.3	120	2749.3	1994
DMU4	194	128.7	255	340.3	592.8	43.5	4072	1414.4
DMU5	245	451	390	1731.4	1585	211	6177.5	2213.5
DMU6	225	2510.9	416.5	861.5	968.5	49.5	6482	1936.7
DMU8	166	1316.05	537	1312.5	497.7	295.5	5183	1821
DMU9	162	1512.7	757	3369.7	1832.8	172.3	7033.3	3167.3

Table A3: Productivity (hr/cgt) per Department

	CGT	Docking	Hull	Piping	Machinery	OpAc	Electrical	Paint	Technical
DMU1	1002.51	0.124	1.408	0.493	2.547	0.795	0.133	5.710	2.373
DMU2	2243.05	0.078	0.253	0.060	1.128	0.316	0.070	2.447	0.971
DMU3	2068.80	0.068	0.263	0.091	0.104	0.229	0.058	1.329	0.964
DMU4	1425.09	0.136	0.090	0.179	0.239	0.416	0.031	2.857	0.992
DMU5	1347.14	0.182	0.335	0.290	1.285	1.177	0.157	4.586	1.643
DMU6	1424.48	0.158	1.763	0.292	0.605	0.680	0.035	4.550	1.360
DMU8	1336.95	0.124	0.984	0.402	0.982	0.372	0.221	3.877	1.362
DMU9	1078.84	0.150	1.402	0.702	3.123	1.699	0.160	6.519	2.936

Table A4: Total Days per Department

	Docking	Hull	Piping	Machinery	OpAc	Electrical	Paint	Technical
DMU1	17	79	30	141	61	17	102	114
DMU2	17	37	12	84	53	18	101	102
DMU3	12	48	25	19	40	23	91	118
DMU4	23	15	23	21	40	17	66	84
DMU5	32	38	33	81	87	33	169	167
DMU6	26	64	30	41	57	15	136	155
DMU8	19	56	32	72	44	33	100	99
DMU9	24	78	61	138	116	21	153	156

Table A5: Bootstrap Results – Docking

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	70.59	60.27	63.54	41.18	70.97
DMU2	88.13	79.15	76.54	76.25	89.09
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	52.17	41.64	44.66	16.31	52.73
DMU5	37.61	28.97	31.19	9.35	38.11
DMU6	46.15	37.44	40.23	16.00	46.56
DMU8	63.16	54.76	57.46	31.55	63.47
DMU9	50.00	41.04	44.02	18.00	50.37

Table A6: Bootstrap Results – Hull

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	18.99	5.80	9.69	-18.40	19.34
DMU2	40.54	2.93	-5.75	-18.92	42.26
DMU3	34.33	-10.87	-19.57	-31.35	35.95
DMU4	100.00	100.00	100.00	100.00	100.00
DMU5	39.47	1.11	-4.86	-21.05	41.09
DMU6	23.44	8.96	15.04	-21.22	23.72
DMU8	26.79	6.80	10.96	-28.48	27.44
DMU9	19.23	0.49	-0.23	-27.85	19.65

Table A7: Bootstrap Results – Piping

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	40.00	22.70	26.66	-12.96	40.43
DMU2	100.00	100.00	100.00	100.00	100.00
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	52.17	29.00	31.26	4.35	53.12
DMU5	49.14	25.55	29.04	-1.72	51.24
DMU6	40.00	26.09	29.79	-3.97	40.61
DMU8	37.50	20.26	23.65	-12.94	38.13
DMU9	19.67	13.49	15.26	-1.64	19.96

Table A8: Bootstrap Results – Machinery

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	13.47	7.99	10.00	-13.02	13.59
DMU2	22.62	11.13	14.72	-25.17	22.97
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	90.48	81.34	80.95	80.95	92.62
DMU5	23.46	10.80	14.46	-27.05	23.81
DMU6	46.34	13.25	13.37	-7.32	47.62
DMU8	26.39	12.89	17.20	-29.24	26.80
DMU9	13.77	8.37	10.46	-13.30	13.87

Table A9: Bootstrap Results – Operational Activity

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	65.57	57.21	58.74	38.01	65.88
DMU2	75.47	61.92	62.89	50.94	75.92
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	100.00	100.00	100.00	100.00	100.00
DMU5	45.98	42.79	43.58	34.72	46.06
DMU6	70.18	64.78	65.81	52.88	70.36
DMU8	100.00	100.00	100.00	100.00	100.00
DMU9	34.48	31.65	32.16	24.89	34.57

Table A10: Bootstrap Results – Electrical

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	88.24	81.51	81.57	76.47	88.44
DMU2	83.33	74.95	75.47	66.67	83.59
DMU3	65.22	55.81	57.67	32.29	65.54
DMU4	100.00	100.00	100.00	100.00	100.00
DMU5	45.45	42.11	42.88	34.57	45.56
DMU6	100.00	100.00	100.00	100.00	100.00
DMU8	45.45	42.53	43.30	35.41	45.54
DMU9	71.43	67.26	68.59	55.95	71.53

Table A11: Bootstrap Results – Paint

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	67.81	57.48	60.19	35.62	68.27
DMU2	75.29	61.38	61.59	50.58	76.13
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	100.00	100.00	100.00	100.00	100.00
DMU5	43.54	32.90	33.83	17.15	44.09
DMU6	59.41	44.84	46.75	21.36	60.29
DMU8	67.49	55.40	57.53	34.97	68.29
DMU9	45.21	37.71	39.51	22.78	45.80

Table A12: Bootstrap Results – Technical

DMU	Efficiency	Bootstrap Mean	Bootstrap Median	Bootstrap Lbound	Bootstrap Ubound
DMU1	73.68	69.03	70.53	54.83	73.81
DMU2	100.00	100.00	100.00	100.00	100.00
DMU3	100.00	100.00	100.00	100.00	100.00
DMU4	100.00	100.00	100.00	100.00	100.00
DMU5	59.30	55.28	56.21	45.18	59.62
DMU6	100.00	100.00	100.00	100.00	100.00
DMU8	84.85	78.41	79.81	69.69	85.03
DMU9	53.84	51.15	51.91	42.47	53.93