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Development of a Quantitative Methodology to Forecast Naval Warship Propulsion Architectures

Brian S. Waller
University of New Orleans, bwaller@uno.edu

Development of a Quantitative Methodology to Forecast Naval Warship Propulsion Architectures

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Dedication

For my parents, Terri and Stephen, who instilled and fostered within me a love of not only the sea, but also the ships that sail them. They calibrated my internal compass early in life, and set me upon the course I have been sailing ever since.

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List of Abbreviations

ASNE	American Society of Naval Engineers
ENMG	Engineering Management
IFEP	Integrated Full Electric Propulsion
IPS	Integrated Power System
kW	kilowatt
kg	kilogram
m/s	meters/second
MGO	Minimal Generator Operations
NAME	Naval Architecture and Marine Engineering
N_{Crew}	Number of Crewmembers Billeted to a Ship
NEEC	Naval Engineering Education Center
NWSC	Naval Surface Warfare Center
PCA	Principal Component Analysis
P_{Elec}	Installed Electrical Power Generation Capacity, in kW
P_{Prop}	Installed Propulsion Power Capacity, in kW
R^2	Coefficient of Determination
R^2_{adj}	Coefficient of Determination, adjusted for degrees of freedom
RN	Royal British Navy
SNAME	Society of Naval Architects and Marine Engineers
SSR	Regression Sum of Squares
SST	Total Correct Sum of Squares
USS	United States Ship
USN	United States Navy
USCG	United States Coast Guard
V_{ship}	Maximum Designed Velocity of the Ship, in m/s

Abstract

This paper is an investigation into a quantitative selection process of either a mechanical or electrical system architecture for the transmission of propulsion power in naval combatant vessels. A database of historical naval ship characteristics was statistically analyzed to determine if there were any predominant ship parameters that could be used to predict whether a ship should be designed with a mechanical power transmission system or an electric one. A Principal Component Analysis was performed to determine the minimum number of dimensions required to define the relationship between the propulsion transmission architecture and the independent variables. Combining the results of the statistical analysis and the PCA, neural networks were trained and tested to separately predict the transmission architecture or the installed electrical generation capacity of a given class of naval combatant.

Keywords: Ship Propulsion; Naval Ship Propulsion; Warship Propulsion; Ship Design Methodology; Preliminary Ship Design Methodology; Electric Ship Propulsion; Electric Ships; Statistical Analysis of Naval Database; Ship Propulsion Architecture; Propulsion Architecture Selection; Forecasting Ship Propulsion.

Introduction and Background

Transmission of Shipboard Propulsion Power

There are four types of propulsion systems installed onboard naval ships. They include mechanical drive, electrical drive, integrated electric drive and all electric ships [1]. Those drive types can be classified into different system architectures based on how they transfer the propulsion power from the prime mover to the propulsion device. These system architectures utilize either a mechanical transmission or an electrical transmission method to provide the ship with propulsion power. All three types of electric drive ships fall into the electrical transmission of power category since the prime mover is connected to an electrical generator, and is not mechanically linked to the propeller by a mechanical shaft.

However, the majority of naval ships in the 20th century were traditionally designed with a mechanical system to transfer the power generated by the prime movers to the propulsion devices [2, 3]. The prime movers included steam boilers and turbines, diesel internal combustion engines, and turbine combustion engines. Even most nuclear powered surface ships utilize steam turbines with mechanical linkages to the propellers. These different types of prime movers would be physically connected to propellers directly through propulsion shafts or first through reduction gear sets that would allow the propeller to operate at lower rotational speeds than those of the prime mover. In more recent US Navy ship designs, the propulsion plant selected for conventional (non-nuclear) ships has primarily been gas turbines due to their high power density levels [4].

This mechanical transmission of propulsion power required that the prime movers be installed inline with the propulsion device, usually a propeller on naval surface combatants. These mechanical transmission arrangements could achieve extremely high power transmission efficiency values, upwards of 95%, but usually only over a small range of speeds near the upper level vessel's top speed [5]. At lower cruise and loiter speeds, which has been shown to be more often than original design operating profiles suggested [6], these mechanical transmissions have much lower transfer efficiency values. In addition, the requirement for the prime movers to be in line with the propulsor greatly limited how the prime movers could be arranged within the hull of the ship. Alternatively, complex reduction and redirection gears could be utilized to offset the centerline of the prime mover from that of the propulsor, in both the horizontal and vertical planes. These gear sets added weight and complexity to the propulsion system, while also decreasing the design's power transmission efficiency [5].

Electric Transmission of Propulsion Power

Electric power has been utilized onboard ships for well over 100 years. In 1883 the US Navy first installed a 110-volt direct current circuit with 247 lamps to light the USS Trenton. Although it started with simple direct current lighting systems, by World War I developments in power generation and distribution had expanded electrical capacities to include alternating current circuits powering pumps, ventilation, and other auxiliary systems [7]. Even the US Navy first utilized an electric propulsion motor on one of the first aircraft carriers, the USS Jupiter, in 1913.

While there have been several types of naval ships built with electric propulsion motors since the USS Jupiter, large electric propulsion motors have only recently become powerful enough, reliable enough, and have suitable noise and heat signatures to become commonly accepted for use in major naval combatants. Due to this relatively recent technological improvement, only a small number of ship classes have been designed to transmit their propulsion power through electrical connections instead of a mechanical shaft or reduction gear set [3].

In an electric drive ship design there is still a short mechanical shaft from the electric motor to the propulsor, however this paper classifies an electric transmission ship as one where the transmission of propulsion power from the prime mover to the propulsion unit(s) is through electric cables instead of a long mechanical shaft arrangement. This allows a ship's prime movers to be installed virtually anywhere onboard the vessel, since the prime mover's placement is not limited by the alignment to a long mechanical propulsion shaft. This flexibility in the general arrangements of a vessel is one of the major positive attributes associated with an electric transmission ship design.

In the commercial sector, electric propulsion system architectures have become very popular on several types of vessels. The cruise industry currently utilizes almost exclusively electric drive ships, in part due to their flexibility in the arrangement of the propulsion system [8]. Another benefit is the ability to supply considerably larger quantities of electric power for the high ship service loads required onboard modern large cruise ships. Even several types of larger bulk carrier vessels have been designed with electric drive systems. The reasons for selecting electric drive for commercial ships varies across different industries, however it is becoming more commonplace thanks to improvements in commercial off the shelf electric drive systems.

Shipboard Electrical Load Demands

When ships first installed electrical generators onboard, the uses of electrical power were limited to simple lighting circuits and early pumping systems. On most large commercial cargo or tanker vessels, these hotel and ship service load requirements have changed little, and therefore electric load requirements have not experienced the same expansion as other types of ships. In the cruise industry, the hotel and service loads are considerable higher, since the vessel is supporting many thousands of people instead of only a few dozen crewmen on merchant ships. However, even with all of those passengers onboard, the electrical load per person is still lower than that of a naval combatant vessel.

With the advances in combat systems since World War II, naval ships have experienced an exponential growth in the amount of electrical load required to operate all of the vessel's systems that continues to increase more every day. Combat systems such as surface search radars, air search radars, point defense targeting systems, targeting and guidance computers and other modern technological improvements require considerably more power than their earlier designs or mechanical predecessors. With efforts to reduce crew sizes on naval combatants, more and more automated control and monitoring systems are being employed. In addition, with fewer and fewer ships utilizing steam boilers for propulsion, most modern naval combatants have converted all of their auxiliary systems, including pumps, environmental control systems (HVAC), and galley equipment, from steam powered to electrically powered units.

All of these efforts combine into ships whose electrical loads for hotel and ship service systems begin to enter the range of propulsion power loads in terms of kilo or even megawatts. Currently, the US Navy is developing new technological and combat systems that create even higher electrical load demands. Some examples include electromagnetic rail guns, electric discharge weapons, and electromagnetic aircraft catapults. While most of these high electrical load systems would seem to be far-fetched futuristic fantasies, all three are currently in the developmental stages by the US Navy. In fact, while at the ASNE Day 2014 conference in Crystal City, VA, the author sat in on several panels that discussed the current progress of those developments, and how they would impact the future of ship design. During one of the presentations it was suggested that an electromagnetic rail gun would require approximately 34MW of power to sustain the full rate of fire that the current design is capable of. The author's attendance at the ASNE Day 2014 event was sponsored by NEEC in order to present a poster on this thesis at the Student Poster event.

Integrated Full Electric Propulsion Ships (IFEP)

When the electrical loads of a vessel begin to reach levels proportional to the propulsion load, such as in the rail gun example, ship designers need to take a hard look at how those electrical power generation needs are being met. As a result, over the past several decades the USN has invested in a large amount of time and money into researching, developing, and implementing all electric surface ships. These all electric ships not only utilize electric propulsion systems, they also utilize a concept known as Integrated Full Electric Propulsion (IFEP). IFEP is a system architecture where the propulsion system prime movers are not just utilized for the required propulsion power, but for all power requirements onboard the ship. Electrical power is generated and supplied to a common ship service grid to which all electrical loads can then be connected [1,8].

These integrated power grid systems are very similar to the land-based power grid networks that power your home [1]. All of the power requirements for the ship are supplied from that common grid, including main propulsion, auxiliary systems, environmental systems, and electronic combat systems like radars and communications equipment. The power can be generated by any number of generation sources, which is another of the qualitative benefits of electrical transmission system architectures. When a generator is taken offline, either as planned for maintenance or in response to a casualty, another generator can be brought online to maintain the level of power generation required to meet the load demand. This adaptability is another qualitative benefit commonly discussed in regards to electrical transmission propulsion systems.

Since these grids allow a ship to be designed with a number of smaller power generators instead of one or two extremely large ones, they can be utilized in a far more fuel efficient manner [1]. By only operating the minimum number of generators to supply the amount of power required at that particular moment in time, these ships can achieve greater fuel efficiency since they are operating closer to their maximum rating and efficiency at any given time. This concept is referred to as Minimum Generator Operation (MGO) [8]. If more power is required, such as an increase in speed or a powerful radar being turned on, additional generators can be quickly brought online to supply the additional power levels.

The flexibility inherent to the ships designed with IFEP allows them to customize the plant configuration to meet the electrical needs of the conditions they are experiencing instead of an arbitrary "operating point" conceived as part of the original design process. In addition, this flexibility is often touted as a distinct advantage onboard a combatant vessel where combat damage and casualties are expected to occur. Having the power generation sources dispersed in smaller

mechanical spaces throughout the ship, instead of concentrated in one or two large compartments near amidships, increases the chances that one or more of the generators will survive the damage and enable the ship to continue functioning.

Integrated Power System (IPS)

The USN has taken the integrated electric ship concept a step farther. They have also developed an Integrated Power System (IPS). IPS utilizes standardized power generation, transmission, and storage equipment across the entire US fleet of ships, not just within a single class of vessel. This standardization will theoretically enable more efficient training of personnel, simplify initial procurement and design of vessels, and streamline the logistical supply of spare parts across the entire US Navy fleet.

The first ship to be designed with the IPS concept is the USS Zumwalt (DDG 1000). Despite being an unproven concept thus far, the IPS idea is based on the Navy's standardization of conventional (non-nuclear) prime movers to a single type of gas turbine utilized across the entire fleet, the LM2500. Since personnel only need to be trained to service one type of prime mover, they can transition between vessel classes with far less training and familiarization time. And since all of the ship classes require the same spare parts, inventories can be combined and reduced instead of stocking different parts for each specific class. However, until more ships are built using IPS systems and the decreased inventory and training costs are calculated, the arguments for adopting the IPS concept will remain a qualitative discussion.

Impact of Propulsion Power Transmission on Early Stage Ship Design

There are many crucial factors that go into the design of a naval combatant vessel. Very early in the design stage the designers are focused on general parameters and requirements that drive the characteristics of the ship, such as the desired top speed intended for the final design. When combined with other preliminary design characteristics, such as the selected hull form, the amount of propulsion power required can begin to be estimated with acceptable accuracy. According to SNAME's *Ship Design and Construction*, one of the next preliminary decisions in the design process is deciding how many shafts and what type of propulsion plant will be installed [4].

The naval architecture design spiral can go through several iterations before a hull design's estimated resistance is known and the marine engineering design cycle can begin in earnest. This means that in a traditional design spiral, the hull shape is analyzed and selected before any significant thought is given to the propulsion system that will be used in that hull. Since traditional

naval combatants have rather narrow underwater hull shapes close to the transom, there is often only enough room to fit the large prime movers near amidships. In fact, many naval combatant design guides identify the "middle third" of the ship as being reserved for the propulsion plant and other auxiliary systems [4]. In traditional mechanical transmission designs this necessitates long drive shafts, which stretch over a significant length of the ship in order to reach the propellers. It also makes for highly predictable naval combatant designs, and makes the machinery spaces of a vessel easier to identify and target in combat scenarios.

There are many other qualitative arguments made in favor of an electrical propulsion architecture over a traditional mechanical one. Many are mission or type specific attributes, such as the unique advantages of an electrical drive ship operating in polar regions where ice is possible. Since the traditional mechanical linkage between the prime mover and the propeller has a limited amount of shock absorption capability, any sudden impacts of foreign debris on the propeller, such as a large ice chunk, can bind the propulsion system and break several, if not most, of the components. Most often this will result in broken propeller blades, sheared propeller shafts, damaged reduction gears, or all of the above.

However, on electric drive ships the very design of the electric propulsion motor allows for a temporary ability of the electric motor to absorb the increase in torque by slipping. Extensive damage can still be done if the condition is not recognized and corrected very quickly, however since the motor's rotor is magnetically linked to the stator, instead of mechanically fixed, the sudden increase in torque does not result in immediate catastrophic damage to the entire drive train. Many modern icebreakers, including two classes of US Coast Guard icebreakers, are designed with electric transmission systems with this in mind.

Much like a ship's operational profile is used to help design the propulsion system, electrical load conditions are used in designing and sizing the electrical power generation capacity of a ship design. When designed as an integrated full electric ship (IFEP) any electrical loads can be met by the same power generation units being utilized to meet the vessel's propulsion loads. This eliminates the need for power generation equipment other than the prime mover(s) to be running at the same time, reducing the amount of maintenance required and fuel consumed by underutilized generators operating below their ideal loading condition [8]. It also allows integrated electric ships to support considerably higher levels of power demanded by higher loading conditions. These increased electrical loads demands can come from any combination of sources, but on a naval combatant they include more powerful combat radar systems, electrical aircraft launch and recovery systems, and even the seemingly futuristic energy discharge weapons currently under development.

On naval combatants, where combat casualties and damage are expected to occur, a resilient design offers redundant power transmission pathways to re-route power around damaged sections of the ship [9]. When ships designed with a mechanical propulsion architecture suffer any damage to an individual component of the propulsion system if affects the capacity of the entire system, potentially even eliminating all of the vessel's maneuvering capability. If the machinery space containing the prime mover floods, there is ordinarily no way to connect a different prime mover to the shaft and return propulsion capability to the ship. Some complex reduction gear assemblies allow for this type of rerouting the propulsion power from other prime movers, however those alternative prime movers are usually located in the same watertight compartment as the original prime mover and would also be affected by any flooding.

When combined with other advances in shipboard power system design, such as zonal distribution of power, electric propulsion architecture once again showcases unique flexibility. Zonal designs isolate sections of the ship into isolated self-contained zones that can operate completely independently of the others. When necessary, these zones can be connected to electrical buses that run the length of the ship, linking each of the zones to the others. In order to preserve this ability in combat situations, these buses are separated from each other, usually on opposite sides of the ship and on different decks [9]. When not in combat, these systems can be interlinked, much like land-based power networks, and MGO fuel saving operations can be resumed. On a ship designed with zonal distribution of power and an integrated electric drive, so long as one power generator remained operational and one of the redundant power transmission lines remain intact, power can be supplied to the propulsion motor and the ship can continue to maneuver.

If the shape of the hull is fixed before any thought is given to the type of propulsion system, the distinct advantages of an electrical transmission system's flexibility and resiliency cannot be utilized to the greatest extent, and the overall design might be limited to more conventional lines of thinking. So in order to maximize the inherent flexibility of an electrical transmission architecture, the propulsion system should be considered as early in the design spiral as possible. However this poses a very important question that this paper attempts to answer: "Is it possible to determine or predict which propulsion transmission method is most likely to be installed on a vessel when only the early vessel characteristics are known?"

This paper documents an investigation into the proposed concept that it is possible to predict the optimal transmission system using some combination of preliminary design characteristics, based on statistical analysis and forecasting of a database comprised of existing naval combatant vessels. This alternative design methodology would enable ship designers to incorporate a preliminary marine engineering design cycle as part of the hull form design in order to maximize the benefits associated with electrical propulsion system architectures without having to know all of a ship's finalized design characteristics.

Statistical Literature and Theory Review

Statistical Literature Review

There were several statistical analysis sources utilized by the author throughout the investigation documented in this paper. Many of them were used by the author to refresh previously learned analysis techniques, while some were used to learn the more advanced methods necessary to complete the analysis of the historical database. These sources and the support they provided the paper are discussed below.

Once the author selected a quantitative approach to determining a relationship between the propulsion system architecture and known ship parameters, the Schaum's Outline Series of statistical texts were obtained and used to refresh the author's statistical analysis skills. Three individual books in this series were obtained, including the fourth edition of *Statistics* [10] and the second editions of *Operations Research* [11] and *Operations Management* [12]. All three texts are published by McGraw Hill.

The Schaum's *Statistics* text was used as an initial primer to brush off and refresh the statistical knowledge the author has not used since obtaining his bachelor's degree several years ago. Concepts such as measures of central tendency (mean, mode, median, etc.) and small sampling were reviewed and tested using the practice problems included as part of the text [10]. Because the number of sample ships utilized in this research was limited to less than 50, and in some cases as few as 9, the statistical analysis performed required as much information for each sample as possible to increase the statistical accuracy of the results.

The basis of the approach used in this analysis was using historical data to predict the value (configuration) of a future asset. Therefore, Schaum's *Operations Research* was obtained and used specifically for Chapter 16: Forecasting. While informative for basic methods of simple forecasting models, the text did not cover the multivariable regressions or forecasting techniques that would be required in the author's approach to forecasting the power transmission architecture of a ship [11].

Similarly, Schaum's *Operations Management* was also obtained for the single chapter pertaining to Forecasting, chapter 4. This text focused on when to use forecasting and determining when it would be beneficial compared to the increasing cost of improving the forecast results. The author also utilized Ch. 3, which reviewed the construction and use of statistical models to represent real world problems or scenarios [12]. Once again, the Schaum's outlines were found to be good reviews of major concepts, but lacked sufficient detail on the more advanced techniques and approaches that would be necessary to draw meaningful conclusions from the database created as part of this thesis.

As part of the Engineering Management curriculum at UNO the author took the ENMG 6112 Quantitative Analysis II course, which provided him with more exposure to Operations Management concepts and analysis methods. The text for this course was *Making Hard Decisions* [13]. Both the course and the text covered modeling decisions, such as the selection of a propulsion system architecture on a naval combatant, and then performing sensitivity and risk analyses of those models.

In addition, the *Making Hard Decisions* textbook [13] came with the DecisionTools® suite of software from the Palisade Corporation [14]. DecisionTools® contains a series of macro programs that run in Microsoft Excel worksheets and enable the user to perform multiple types of Operations Management analyses. Some of the macros include PrecisionTree®, used for creating decision tree and influence diagrams, and StatTools®, which is used to perform statistical analysis on databases created in an Excel worksheet. The ENMG 6112 course served as an introduction to the software and analysis methods, which the author expanded upon in the course of the investigation into this thesis. Although not covered in ENMG 6112, DecisionTools® also included StatTools® and NeuralNet®, both of which were utilized in the course of the analysis documented in this paper.

The author also used *Probability & Statistics for Engineers & Scientists* [15], which he originally obtained for an advanced engineering math course as part of his bachelor's degree at the US Coast Guard Academy in 2007. This book provided much more information on many of the topics only briefly discussed in the Schaum's Outlines series, and was used as an alternative source of guidance throughout the data analysis process until it was determined that neural networks would be required to establish and define the relationships.

The author was referred to *A Tutorial on Principal Component Analysis* [16] and *Lecture 9: Principal Component Analysis* [17] by his professor in order to learn the concepts behind Principal Component Analysis and its effectiveness at reducing datasets to lower dimensions, thereby reducing the complexity involved with defining the problem. These two sources presented PCA in a relatively simple manner that would not overwhelm someone learning about PCA for the first time.

Statistical Theory Review

Statistics is a form of data analysis where information is analyzed to find trends or patterns that can be used to determine the effectiveness of a process, monitor performances, or even predict an unknown value, all based on the relationships between the types of information gathered. The information is gathered in the form of observations or samples compiled in a database that can then be analyzed using various statistical methods. These individual methods vary in their effectiveness, and need to be utilized as part of a broader analysis in order to maximize their influence on making decisions based on the trends revealed by the analysis process as a whole [14, 15].

Designing and constructing two identical ships with different propulsion system architectures would be exceedingly expensive and impractical. Traditional self-propelled model tests simulate mechanical propulsion architectures with miniature electric motors programmed to behave like a mechanical system. These factors combine to make designing an experiment to determine the appropriate propulsion system architecture exceedingly difficult.

With these factors in mind, the author approached the problem of forecasting or predicting the propulsion system architecture using a retrospective study. This study analyzed a historical database of characteristics for existing classes of naval combatants. While inexpensive compared to the experimentally based data collection methods briefly mentioned above, reliance on historical data has several disadvantages as well. For instance, the validity and reliability of the historical data is often unknown, since the individual analyzing the information is often not the original collector of the data. There may be errors in either the sources where the data was found, or the original collection may have been flawed, and the analyzer will probably not be aware of the errors. There are often also critical gaps in the information available, and the missing values have to either be ignored or predicted using probability distributions or neural networks, both of which introduce uncertainty into a statistical analysis [15].

The data collected for this analysis was collected from several different sources and cross checked in an attempt to eliminate gaps and errors. This is discussed in further detail in the Methodology section; however the author cannot guarantee that all possible errors were eliminated since he was not the original recorder of the information, merely its collector. Even with the validation of information through multiple sources, several important categories of information have large gaps that dictated which variables could ultimately be selected as part of the historical analysis.

Descriptive Statistics

Once the information is compiled into a database, descriptive statistics can be calculated in order to present a summary of the data being analyzed. These are also called single-number statistics, and include commonly recognized names like means, medians, and standard deviations [15]. These single-number statistics are separated into two different categories based on what information they provide about the database.

The first category is "Measures of Location." These statistics values provide a statistical analyst with a quantifiable measure of where the information is centered. There are two major measures of location, the mean and the median. The mean is a numerical average that shows where the weighted center of a series of observations is located. The median, however, demonstrates the central tendency of the sample data without being influenced by outliers or extreme values that can skew the numerical average. Additional measures of location exist, but they are less common and were not utilized as part of this paper.

The mean can also be used to compare two populations of data, in this case ships with electrical propulsion architectures and those with mechanical architectures. This is a common method to decide between two choices, but it relies on relatively large sample sizes or normally distributed data in order to be considered accurate. As discussed in later sections of this paper, the number of available electrical architecture ships was only 9, which is well below the recommended sample size of 30. Even with a small number of samples, if the data is distributed in a normal fashion reasonable approximations of a normal distribution can be achieved [15]. Since the data collected on historical ships was not normally distributed for most of the values, the samples had to be "normalized" to the largest value in order to ensure the accuracy of the analysis performed.

The second category of descriptive statistics is "Measures of Variability." These values seek to describe how the data is spread out or distributed rather than where it is centered. They include the sample range, standard deviation, and variance. The range is a simple calculation of the highest value minus the lowest value, and is used extensively in the statistical quality control of a process [15]. The variance of the data (s^2) is calculated by equation (2.1) and measures how far each individual sample (x_i) is from the mean ($\bar{x}$). The standard deviation (s) is the square root of the variance of the data, as shown in equation (2.2), and is probably the most commonly used measure of variability [15]. The use of standard deviation is considered easier since it is represented in linear units instead of squared units. According to [15], the variance is considered more in inferential theory, whereas the standard deviation is used more in practical applications.

$$s^2 = \sum_{i=1}^{n} \frac{(x_i - \bar{x})^2}{n-1} \qquad (2.1)$$

$$s = \sqrt{s^2} \qquad (2.2)$$

Statistical Models

These descriptive statistics provide important summaries about the data collected, but it is often hard to draw conclusions from these individual calculations. In order to find meaningful relationships between the data points statistical inference methods will need to be incorporated with the results of the descriptive statistics. These statistical methods are combined to form a statistical model that represents the data being analyzed. The models take different forms, and provide the analyst with information in several different formats. The selection of one type or another of model to describe the data is heavily based on what the analyst is trying to prove or disprove, and is often accompanied by fundamental assumptions about the nature of the data collected. Of particular interest to this paper are the exploratory data analysis models and regression models.

Exploratory data analysis models are also known as graphical models. They rely on plots, charts, and other graphics to visually display information for the analyst to draw conclusions. These various types of graphics are most often used to call attention to violated assumptions that would otherwise go unnoticed by the analyst [15]. For example, if an analyst made a fundamental assumption that two ship parameters were related in a linear fashion, a plot of the two variables might reveal they were actually exponentially related.

Simple two dimensional plots of sample observations can be used to determine relationships between the variables included in a database. Several of these comparison plots were created as part of this analysis and are discussed in the Results section. These plots are of limited use when there are multiple interdependencies between variables, as is often the case when examining ship characteristics. Because these interdependencies can often involve more than 3 variables, it becomes impossible to plot them in a way that an analyst can readily interpret the relationship.

Another form of graphical model is the relative frequency diagram, also known as the histogram. These histograms separate the samples of a particular variable into "bins" that contain a range of values. This summarizes the data distribution and enables the analyst to determine if their collection of data is skewed to one side or the other of the mean value [15]. Histograms of the major variables considered in this analysis are included as part of Appendix B, and discussed in the Results section.

Regression models look for numerical trends and inherent relationships in the data that can be described through various forms of equations. The specific form of the relationship equation being examined is usually determined by the analyst, often based on the results of the graphical models. The regression model is also usually accompanied by an estimation theory that enables predictions to be made regarding unknown data points within the statistical range of the regression model [15]. The goal of the regression is to explain or predict the value of a dependent variable through the use of independent variables or regressors [15]. The most common form of regression analysis is a simple regression, which utilizes the linear form shown in equation 2.3 to describe the relationship between the dependent variable y and the regressor x using the coefficients of m and b. The intercept of the line is represented by b, while the slope of the line is given my m.

$$y = mx + b \qquad (2.3)$$

In order to match this equation to the distributed sample data, a regression framework needs to be selected. The most frequently used framework is the Least Squares method. The Least Squares method is based on the concept of minimizing errors for a particular set of regression coefficients. These errors are referred to as residuals, and are calculated by subtracting the equation's predicted value of y for a given x with the actual value of y for that sample of x. The residuals for a linear regression are essentially the vertical deviations of a plotted point from the line generated by the regression equation. The Least Squares method produces a regression equation that minimizes the sum of squares of the vertical deviations from the original sample data points.

$$y = b + m_1 x_1 + m_2 x_2 + \cdots + m_k x_k \qquad (2.4)$$

Since most problems being subjected to a regression analysis will likely involve more than one independent variable, the regression methods discussed so far can also be applied to problems with multiple regressors. Equation (2.4) shows the basic linear form for a multivariable regression equation [15]. As the number of regressors is increased, the difficulty in calculating the least squares method is also significantly increased. The use of matrices can significantly help in easing the determination of the coefficients when calculating by hand, however there are many statistical software programs that can perform a least squares method multivariable linear regression analysis for the analyst [15].

Just because a regression determines the equation with the smallest total sum of vertical deviations does not mean that that equation is a good fit to the sample data. One of the metrics used to analyze regression analyses is the coefficient of determination (R^2). The R^2 value of a regression equation describes what proportion of the variance in the sample data is explained by the resulting equation. In the case of multivariable regressions it is referred to as the coefficient of multiple determination, and calculated using the regression sum of squares (SSR) and the total correct sum of squares (SST). The SSR is calculated using equation (2.5) and represents the variability of the sample data that is explained by the regression model. Conversely, the SST is the variation in the dependent value that would be ideally explained by the regression model, and can be calculated with equation (2.6). Equation 2.7 shows how these two values are used to determine the coefficient of determination.

$$SSR = \sum_{i=1}^{n} (\hat{y}_i - \bar{y}_i)^2 \qquad (2.5)$$

$$SST = \sum_{i=1}^{n} (y_i - \bar{y}_i)^2 \qquad (2.6)$$

$$R^2 = \frac{SSR}{SST} \qquad (2.7)$$

The value of R^2 can range from between 0 and 1. The closer the regression model's value of R^2 is to 1, the more accurately the resulting equation models the variance of the sample data being analyzed. However, as with the single-number statistics, it is not only difficult but also unwise to select a regression model based solely on the coefficient of determination [15]. In multivariable regressions another common metric is the adjusted R^2, which is a variation of the coefficient of determination adjusted for the degrees of freedom in the regression model. This variation prevents the R^2 from becoming artificially inflated due to the inclusion of unnecessary additional variables, and is calculated using equation (2.8). Both of these R^2 values can be calculated using most statistical analysis programs, however as mentioned above, they should not be used as the sole criteria for selecting a regression model [15].

$$R_{adj}^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 / (n-k-1)}{SST/(n-1)} \qquad (2.8)$$

Categorical Variables

In many cases numeric variables are not enough to describe the information being statistically analyzed. In these cases, a special class of variables is required. The use of a categorical variable allows for a non-numeric category or description of an item to be included in a numerical analysis such as the regressions discussed in the previous section. These categorical variables are represented in a binary manner as either a 1 or a 0. If the value is listed as a 1, it means the sample or observation belongs to that particular category [14]. In the case of a science experiment, the categorical variable may represent the inclusion of a catalyst in a chemical reaction. If the catalyst was included in an observation, it would be assigned a value of 1. If it was excluded, the observation would have a value of 0. If there are more than two possible conditions, multiple categories are used, but only the one that is true is assigned a value of 1, while the rest are assigned a value of 0 [14].

Principal Component Analysis

Both graphical and regression models were utilized in this paper's retrospective study. However they were not enough to adequately describe the variation of the historical data in terms of the categorical variable of the propulsion system transmission architecture. The next analytical procedure utilized as part of this investigation was a Principal Component Analysis (PCA). PCA is based on linear algebra and is a simple tool to extract meaningful information from seemingly confusing data sets. It can often be used to reduce a dataset to a lower dimension and will sometime even reveal underlying relationships that were masked by the confusion of the larger dataset [16].

Since the retrospective analysis performed in this paper relied upon a database of available historical sample data, it was impossible to know which, if any, variables would be important to determining which propulsion transmission system should be selected for a given design. PCA can be utilized to calculate a new basis to compare the collected data while filtering out noise, imperfections in the data samples, and even reveal hidden dynamics that describe the behavior of the dataset. PCA accomplishes this by changing the reference basis we use to examine the dataset through linear algebra and an assumption that the dataset behaves linearly on a local level [16].

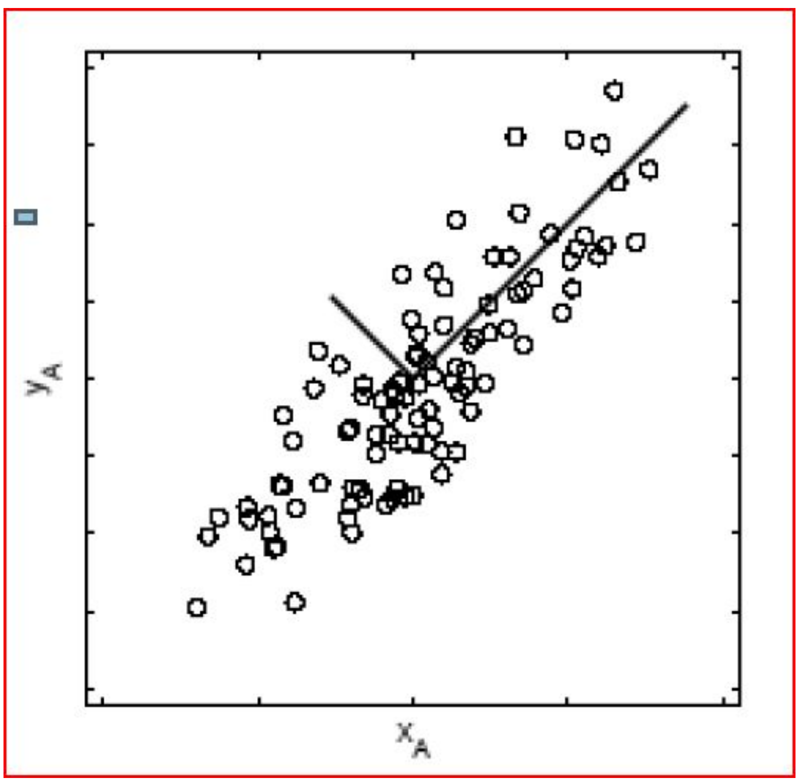

Figure 1: PCA Reorientation of Basis [17]

This change in reference basis can be considered as a rotation and stretching of the axes used to measure the position of a data point. Figure 1 shows a series of observations that are plotted on an x-y chart. PCA determines the linear transformations of the original axes that will best explain the data by maximizing the variance between orthogonal principal components. In Figure 1 these principal components are represented by the two lines at right angles in the cluster of data points. While this seems simple to do and easy to visualize in two dimensions, PCA enables the same process to be done on data sets described by any number of variables and determine how many of those dimensions are truly required to define the underlying dynamic relationship.

The linear algebra behind the PCA process enables a matrix of inputs, or observations, to be transformed by a feature matrix into a matrix of weighted observations. Figure 2 shows the how the covariance matrix of the sample data, labeled as the "input matrix" in Figure 2, is transformed by the feature matrix using linear algebra. In this example, obtained from [17], the samples are the observed data points, the dimensions the variables used to describe the samples, and the features are the principal components used to redefine the observed data points after a change of basis.

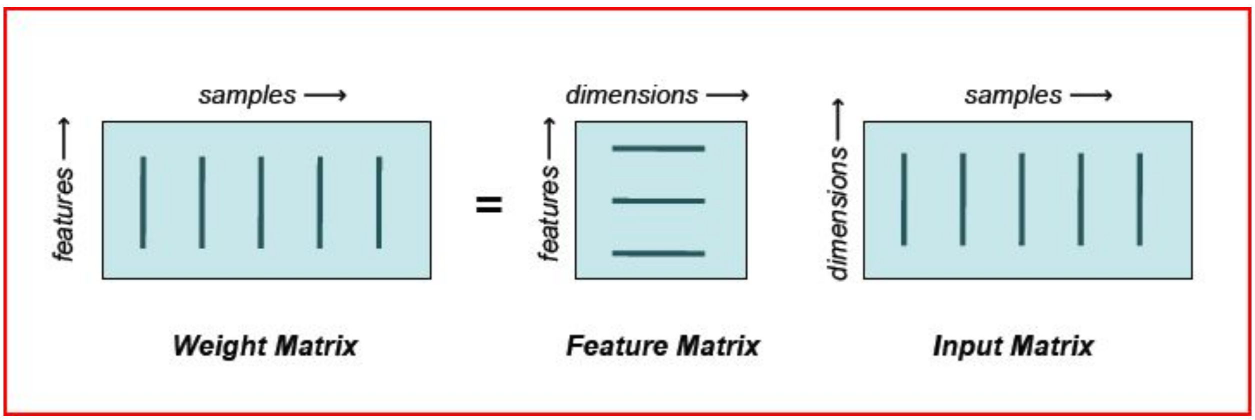

Figure 2: Explanation of PCA's Linear Algebra [17]

The covariance matrix of the input sample data is used in order to eliminate any redundancy recorded by multiple variables that are not entirely independent of each other [16]. The PCA algorithm ultimately calculates the Eigen vectors and Eigen values of the covariance matrix. These Eigen vectors are in fact the principal components that are orthogonal to each other and can best describe the variance of the sample data.

The PCA also allows the principal components to be ranked by how much of the sample data's variance is explained by each principal component. These rankings allow an analyst to determine how many of those principal components are necessary to define the majority of the variance exhibited in the sample data [16]. In many cases there is a significant drop off in the amount of variance accounted for after the first several principal components. These principal components can be eliminated and a reasonable approximation of the original data set can be reconstructed using only the principal components with the highest rankings. This process is commonly used in signal processing to compress images without an appreciable loss in signal quality [17].

Neural Networks

Neural networks are utilized in many fields because of their ability to learn complex relationships within datasets and use them to predict missing values. Similar to the linear regression techniques discussed above, they are utilized for generating a function that approximates the behaviors exhibited by the original data set. Unlike the linear methods of approximation, neural networks are modeled on the way a brain extrapolates information to make predictions [14].

Neural networks are constructed with a series of nodes or neurons, very similar to the neurons in a human brain. Each of these nodes performs a simple portion of the computations within the network then passes the output to the next level of nodes for them to process in another simple computation. The different levels of nodes are referred to as layers. Each layer has multiple nodes. Every neural network will have an input layer and an output layer. In between these two "visible" layers is a series of hidden layers where the computations are performed. Figure 3 displays a typical arrangement of a neural network with two hidden layers. In this example, the first hidden layer has 2 hidden nodes, while the second has three. The exact number of nodes in each layer is determined by the analyst in order to find a neural network with the best fit to the input data [14]. Each arrow in Figure 3 represents a computation performed on the input received from the previous layer of nodes. Neural networks can also be configured and utilized to predict categorical outputs in addition to numeric values. This makes them ideal candidates to predict the propulsion system architecture onboard naval combatants.

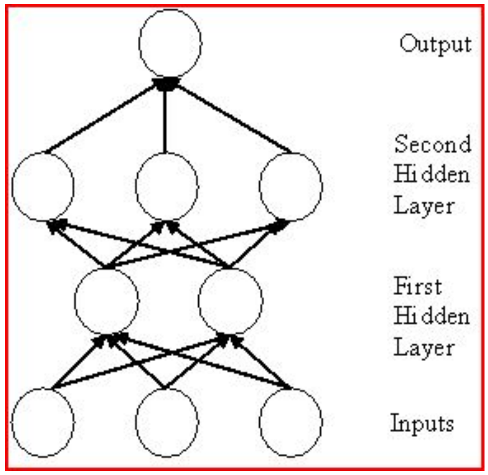

Figure 3: Neural Net Structure [14]

One of the features that make neural networks more powerful than standard statistical analysis methods is their ability to incorporate non-linear activation functions in the hidden layers of the network. Figure 4 shows an alternative visual depiction of a neural network. The first hidden layer utilizes a non-linear activation function, while the second hidden layer utilizes a simple linear computation to the outputs from the first hidden layer of nodes [14]. The inclusion of this non-linear activation function enables the neural network to extrapolate relationships in the dataset that cannot be expressed using linear regression techniques. Figure 4 also shows the first hidden layer of nodes each has its own weight applied to the computation performed along with its own bias that is added to the computation's result. In this example the second layer of nodes is only assigned a weight, no biases are included.

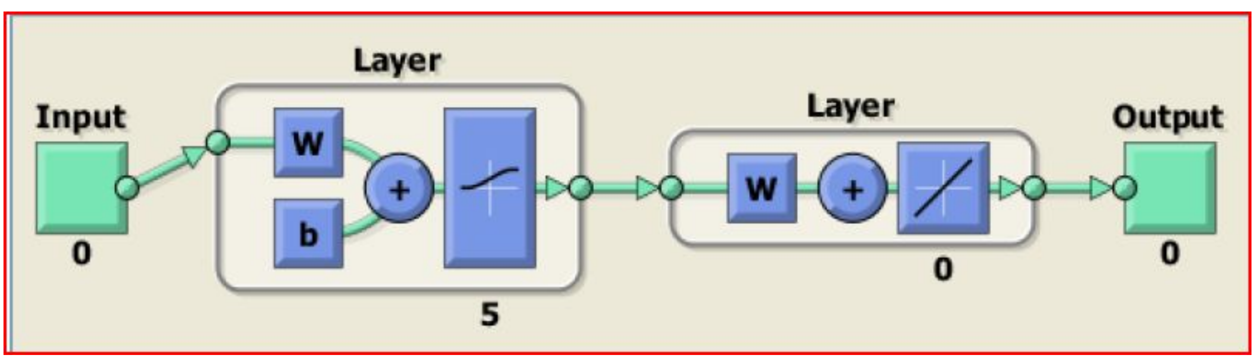

Figure 4: Example Neural Network Layout [14]

Once a neural network configuration is selected, it needs to be trained to the input data. This is done using a training algorithm that compares the output of the neural network to the original input value. The computation performed by each node is summarized in equation (2.9). The in_0 to in_n values are the outputs from the previous layer of nodes, while w_0 to w_n values are the connection weights. Each node has its own bias. The values for each of these weights and biases are determined by the training algorithm selected.

$$Out_{Node} = \sum_0^n (in_0 * w_0 + in_1 * w_1 + \cdots + in_n * w_n + bias) \qquad (2.9)$$

Once the initial inputs are processed into outputs of the network, minor adjustments are made to the weights and biases assigned to each node's computational output, and then the network is retested by the algorithm. This process continues for as many iterations as necessary in order to meet the performance criteria selected by the analyst [14]. One of the most common performance criteria utilized for both numeric and categorical neural networks is the mean square error over all the training cases.

Once the network meets the training criteria selected, a random series of test cases that were set aside during the training process are used to validate the training results. These test cases examine whether the predicted values for the unused samples match the original values within a certain degree of error. If the analyst is satisfied with the both the training and testing results, the trained neural network can then be used to predict unknown or missing values in the dataset [14].

In order to efficiently configure the neural network with an appropriate number of input variables, a PCA is typically used to determine the minimum number of dimensions required to define the sample data. Usually a neural network is designed to model the number of variables selected by the PCA's rankings of the principal components ability to explain the variance of the sample data. While the neural network will not yield a perfect prediction for each observation in the original data set, it can create a reasonable approximation that performs within specific performance criteria selected by the analyst. The resulting matrices of the individual nodes weights and biases can be extracted from the neural network along with the activation function (∅) in order to predict the dependent numeric or categorical variable for additional samples using equation (2.10).

$$\boldsymbol{y} = \left[\sum_{j=1}^{m} \boldsymbol{v_j} \emptyset\left(\sum_{i=1}^{n} \left(\boldsymbol{w_{ji}} \boldsymbol{u_i} + \boldsymbol{b_j}\right)\right) + \boldsymbol{c}\right] \qquad (2.10)$$

Methodology

Approach

Due to the expense associated with building two identical full scale ships, one with an electric and the other mechanical power transmission system, many of the published arguments and discussions for either power transmission system are based on qualitative analysis and reflection instead of quantitative data. In light of this, the author decided to utilize a historical data analysis approach in order to determine if an ideal power transmission method could be identified early in the design stages of a naval combatant.

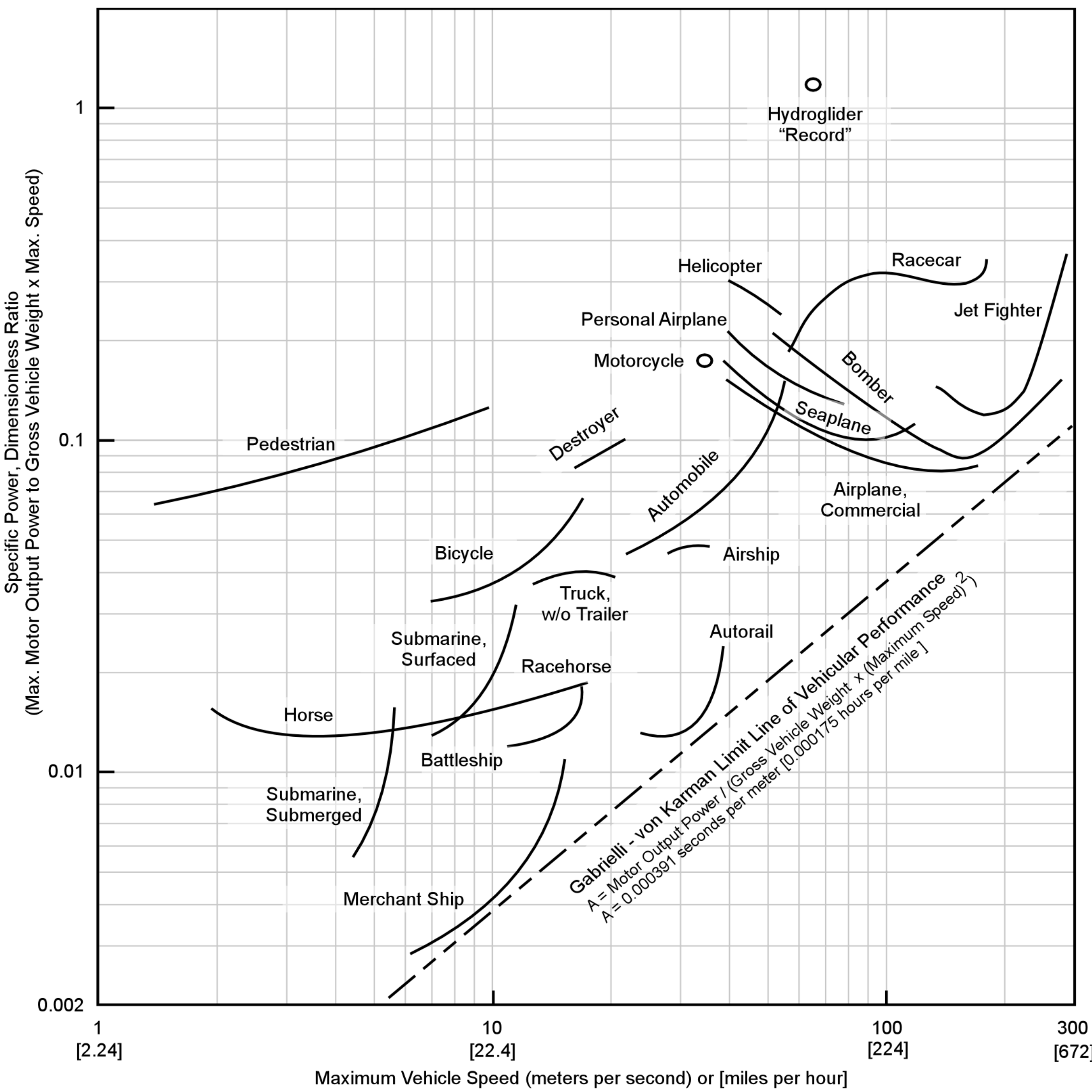

Figure 5: The Von Karmen Diagram [18]

The author was originally inspired to this approach by a lecture given by Dr. Chris McKesson in NAME 4177 Advanced Marine Vehicle Design on Vessel Performance Metrics at the University of New Orleans [18]. In that lesson, the author was introduced to Theodore Von Karmen's equation for transportation efficiency, originally published in Von Karmen's "What Price Speed?" paper. The Von Karmen diagram, shown as Figure 5, displays how different methods of transportation could be identified based on where they fell on this plot of their specific power versus their maximum speed [19]. Based on this plot, the author theorized that there would be some similar combination of metrics that would allow one to predict whether a ship utilized mechanical or electrical transmission of its propulsion power.

In order to perform this analysis, the author first created a database of naval combatant vessels from the US Navy, the US Coast Guard and the Royal British Navy. This database was separated into two groups based on their propulsion power transmission system architecture, and was then statistically analyzed in an investigation to find trends, common features, or other indicators that would lead to the selection of either a mechanical or electrical propulsion transmission architecture. The statistical methods utilized included basic statistics comparisons, two dimensional plots of various variable combinations, correlation tables, and multivariable linear regressions. When those tools did not provide a reliable prediction method, the author performed a Principal Component Analysis (PCA) to determine the minimum number of dimensions required to define the "space" enclosed by the statistical model. Several neural networks were created and trained to would predict the system architecture using the fewest number of input variables required, as determined by the results of the PCA, in order to achieve the desired level of prediction accuracy.

Data Collection

Understandably, most navies are weary of disclosing the specific characteristics of their combatant vessels. This made collecting accurate historical data extremely challenging. Nearly all of the information utilized in this analysis was collected primarily from three sources. The first of these were the publicly available 1986 and 2009 editions of Jane's Fighting Ships [2, 3]. Since the author is an officer in the US Coast Guard, the characteristics of several USCG ship classes, which are publicly available on the Coast Guard's website [20], were also included. The third source of information was Dr. Collen Kennel of the US Navy's Center for Innovation of Ship Design at the Naval Surface Warfare Center (NSWC) in Carderock, MD.

With very few exceptions, all of the naval ships within a particular class have the same general characteristics and propulsion system architecture. Some of the ship classes have "flights" that represent minor changes in design or outfit, such as the Flight 1 and Flight 2 variants of the FFG 51 destroyers in the USN fleet [3]. With this in mind, the data was collected for different classes of ships, instead of the individual ships themselves. This eliminated any disproportional weighting of the characteristics of ship classes with a higher number of ships than the others.

Initially most of the basic information, such as the year a particular class was first commissioned or the class's average displacement, was found in either the 1986 or 2009 edition of Jane's Fighting Ships [2, 3]. The 1986 edition was referenced for some of the ship classes that have since been decommissioned and are no longer included in the more recent editions of Jane's. Being a publicly available reference, more often than not the characteristics for a given type of vessel were not all available from this source. Occasionally some of the information found in Jane's was also found to be inaccurate or underestimated when compared to the other sources. For example, many of the newer classes of ships had speeds listed as "30+ knots" instead of the actual top speed of the class.

As mentioned above, the author also included ship characteristics for 16 classes of USCG cutters, and 3 classes of small boats. During the analysis, the author wound up removing the three small boat classes, as well as one from the US Navy, since they are designed and built in a dramatically different fashion than the other naval combatants being considered. All of the USCG cutter data was collected from the Aircraft, Boats, and Cutters data sheet pages on the USCG's public domain website [20]. Since the USCG fleet is comprised of mostly older vessels, much of this information matched what was listed in the 2009 edition of Jane's [3].

The remainder of the database was then filled in with the US Navy-specific information provided to the author by the USN through Dr. Kennell. Due to the sensitive nature of the ship characteristics, the author agreed to keep the provided information secured on a government computer at a local Coast Guard base. Most of this data was used to confirm the publicly available numbers obtained from Jane's Fighting Ships. But unlike the information available in Jane's, the USN supplied information also included installed electrical power generation capacity for most of the classes of ships, as well as more accurate speed capabilities, displacements and occasionally the designed electrical load conditions.

The author also included the USS Wasp and USS Makin Island, two ships in the same helicopter/landing craft amphibious assault ship class (LHD). The USS Wasp was the first ship in the class, and was designed with a steam boiler as her prime mover that utilized a mechanical transmission system. The USS Makin Island was the eighth ship in the class, and was designed differently from the rest of her class to utilize a hybrid propulsion system combining a mechanical gas turbine primary system coupled with an electric auxiliary propulsion system [21]. For the purpose of this analysis, the USS Makin Island was classified as an electrical transmission ship, even though a mechanical shaft was still utilized for the gas turbine.

After compiling all of the information, the author constructed a database comprised of 51 different classes of surface ships. There were a total of 26 different ship classes from the US Navy, 19 classes from the US Coast Guard, and 5 additional classes from the Royal British Navy. Of those 51 classes, 9 were originally designed with electric transmission of their propulsion power, while the remaining 42 had mechanical transmission systems. Table 1 shows a summary of the ship classes included in the database, broken down by what fleet they belong to and what the purpose of the vessel class is.

Table 1: Breakdown of Naval Combatant Database

Breakdown of Database by Role		Number of Classes:	
Fleet	Ship's Role	Mechanical	Electrical
US Navy	Amphibious Assault Ship	4	2
	Aircraft Carrier	1	-
	Patrol	2	-
	Small Boat	1	-
	Submarine	-	1
	Surface Warfare	10	1
	Other	2	1
US Coast Guard	Buoy Tender	2	1
	Icebreaker	1	2
	Patrol	6	-
	Small Boat	3	-
	Surface Warfare	4	-
	Other	1	-
Royal Navy	Aircraft Carrier	1	-
	Surface Warfare	4	1
	Totals:	42	9

The database was originally comprised of nearly 50 various ship characteristics or parameters. Due to the lack of available information for many of those categories, such as the number and type of prime movers, the author limited the analysis of the database to 20 of the most heavily populated and relevant ship characteristics. Of those remaining variables, 14 are numeric characteristics, and the remaining 6 are categorical values. All of the numeric values were converted into metric units (kg, kW, m/s) in order to ensure accurate comparisons between data obtained from multiple sources.

One of the excluded categories was the Maximum Designed Electrical Load, which the author believes should have a significant role in the selection of the power system architecture. The amount of ship's service electrical power generation capacity installed on a naval vessel is based on the highest electrical load condition the vessel is designed for, plus an additional margin for future growth. Since the information was only available for a small percentage of the ships (~33%) the author was forced to substitute this design parameter for the Installed Electrical Generation Capacity. This growth margin is not always consistently applied on naval vessels, and can range from 5-20% of the highest load condition, therefore the author did not attempt to calculate values for this parameter. Table 2 lists the 20 different characteristics collected from the sources described above and selected for use in this analysis.

Table 2: List of Ship Class Characteristics

Characteristic	Units	Variable Type
Class Name	-	Categorical
Class Commissioned Since	year	Numeric
Propulsion Configuration	-	Categorical
Propulsion Transmission Architecture	Mech or Elec	Categorical
Purpose/Ship Type	-	Categorical
Vessel Weight	kg	Numeric
Speed	m/s	Numeric
Total Installed Power	kW	Numeric
Installed Propulsion Power	kW	Numeric
Installed Electrical Capacity	kW	Numeric
Propulsion Power/Weight	kW/kg	Numeric
Electrical Power/Weight	kW/kg	Numeric
Transport Factor (Specific Power)	dimensionless ratio	Numeric
Volumetric Froude Number	dimensionless ratio	Numeric
Crew Size	# of persons	Numeric
Elec Power/Crew Ratio	kW/person	Numeric
Elec Power/Propulsion Power	kW/person	Numeric

Results

Graphical/Visually Apparent Relationships

The author initially attempted to identify any obvious correlations or trends between individual characteristics of different types of naval ships using two dimensional comparison plots. While yielding several interesting plots, which are included as Appendix A, there were no readily identifiable zones where one type of propulsion transmission architecture appeared more often than the other for a given type of vessel. Figure 6 shows an example of these plots where the installed propulsion power for each type of vessel is plotted against the installed electrical generation capacity, both in kilowatts (kW).

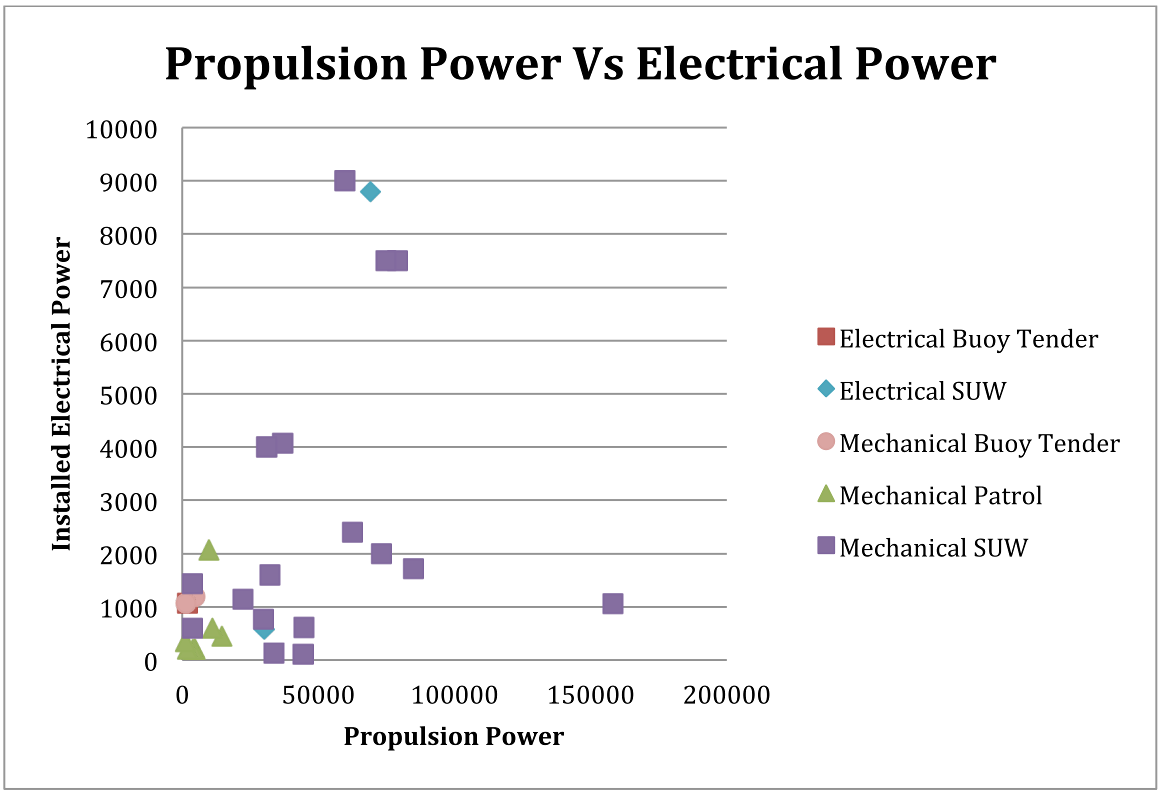

Figure 6: 2-D Plot of Electrical Power Capacity (kW) vs. Propulsion Power (kW)

Figure 6 displays some interesting trends in the relationship between installed propulsion power capacity and electrical generation capacity for vessels of different design purposes, however the electrical and mechanical transmission ships are intermixed, eliminating this relationship as a selection method of the propulsion transmission architecture. These intermixed results hold true for many of the plots included as part of Appendix A.

In an attempt to directly compare to the Von Karmen specific power versus speed plot, the author created another plot comparing the specific power and speed for electrical types of ship and their mechanical counterparts. Figure 7 shows the author's recreation of the Von Karmen plot using the data collected as part of this research, and is plotted on logarithmic axes like the original in Figure 5. Both the electric and mechanical transmission ships of the same vessel type appear in the same region of the plot. After reflecting upon this, it would appear to make sense since the amount of propulsion power required to achieve a given speed with a particular hull shape is the not affected by the type of power transmission architecture utilized in that vessel. This is also supported by the assertion made in [4] that most modern surface combatant speed requirements are driven by the need to cruise in carrier battle groups instead of class-specific mission capabilities.

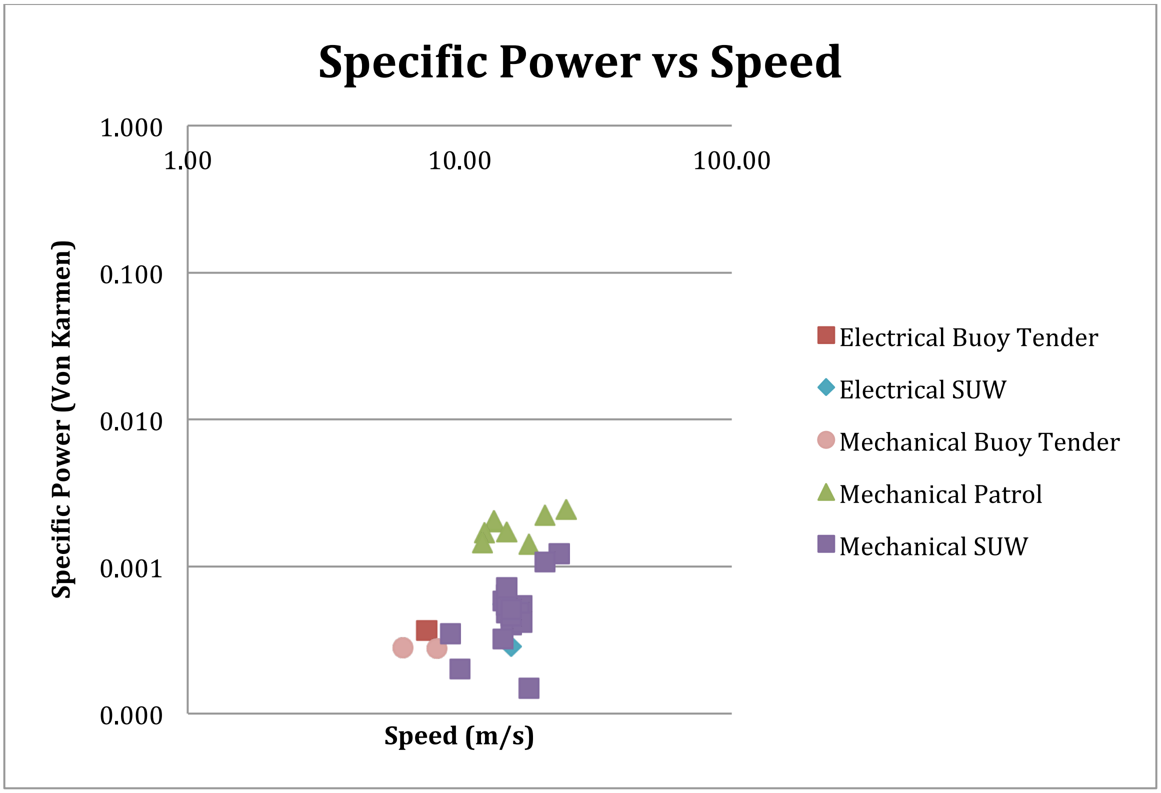

Figure 7: Recreation of the Von Karmen diagram

Next the author attempted to create a series of specific electrical power plots, substituting the propulsion power used in the original Von Karmen diagram for the installed electrical power. However when plotted against speed on logarithmic axes, as is shown in Figure 8, there does not appear to be a strong link between a vessel's speed and installed electrical generation capacity. Therefore this new plot does not help to discern which transmission method should be used by a given vessel. Various other plots were generated comparing specific electrical power to other parameters, however no strong correlations to the propulsion transmission architecture were discovered using this particular graphical technique with specific electrical power.

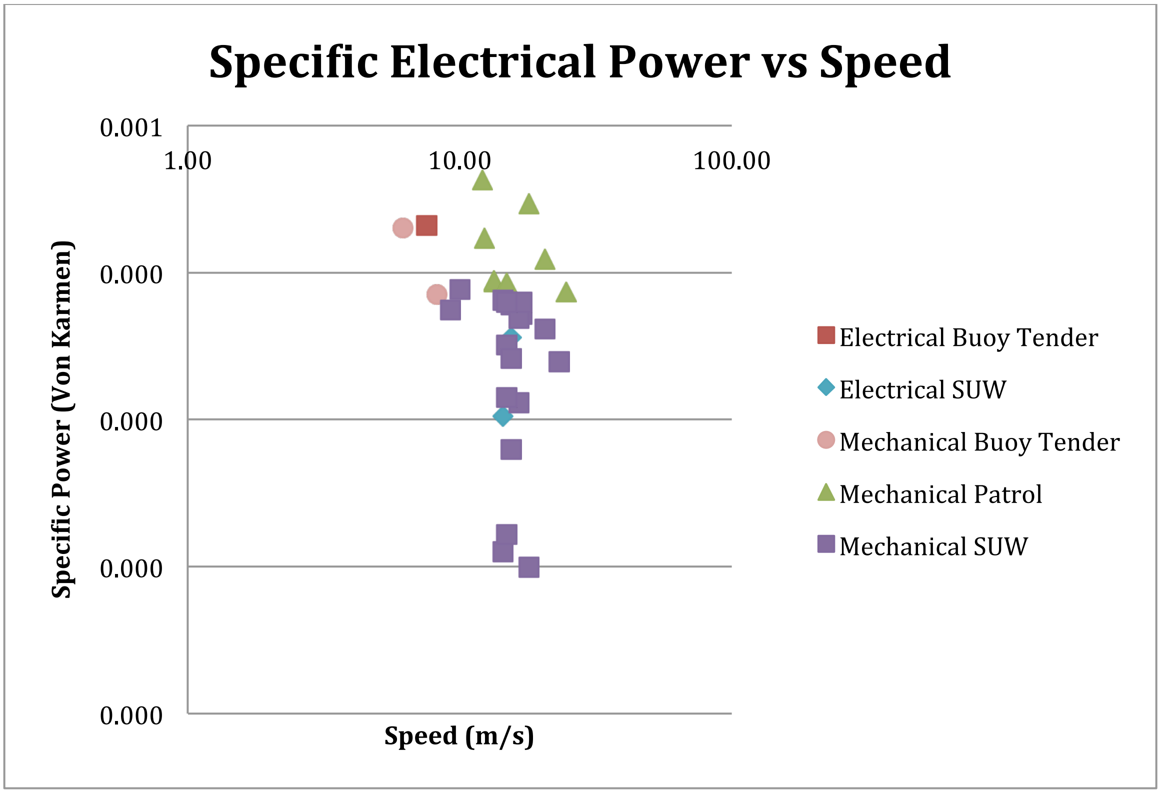

Figure 8: Variation of the Von Karmen Diagram using Specific Electrical Power

Statistical Analysis

Having explored simple two dimensional relationships between the various ship parameters collected, and finding no significant correlations, the author next moved on to descriptive statistical analysis of the available data. This analysis was begun by exploring simple statistical relationships between the parameters collected in the database.

The DecisionTools suite of MS Excel macro programs, available from Palisade [14], was obtained by the author as part of his ENMG 6112 Quantitative Analysis II course, and was the primary statistical analysis software used in this analysis. The author also utilized Matlab for several advanced analysis methods that were beyond the capabilities of the DesicionTools® suite.

The database was initially analyzed one variable at a time to determine the spread of the individual variables. This analysis included calculating the mean, spread, variance, and count for each of the 13 numeric characteristics contained in the database. A complete list of the statistical summaries for each variable in the database is included in Appendix B. Some of the variables have extremely large spreads, especially the vessel weight and installed power categories. This was one of the factors that led the author to eliminate the small boats from the database for the remaining

analysis. The variable summaries were run again for the database excluding the 4 classes of small boats. While the spread of many of the numeric variables was reduced, there are still several variables with maximum values several orders of magnitude larger than the minimum values. This was to be expected since all sizes and types of naval combatant vessels were included in the database. All of the analysis performed from this point on utilized only the 46 samples remaining after the small boats were removed from the database.

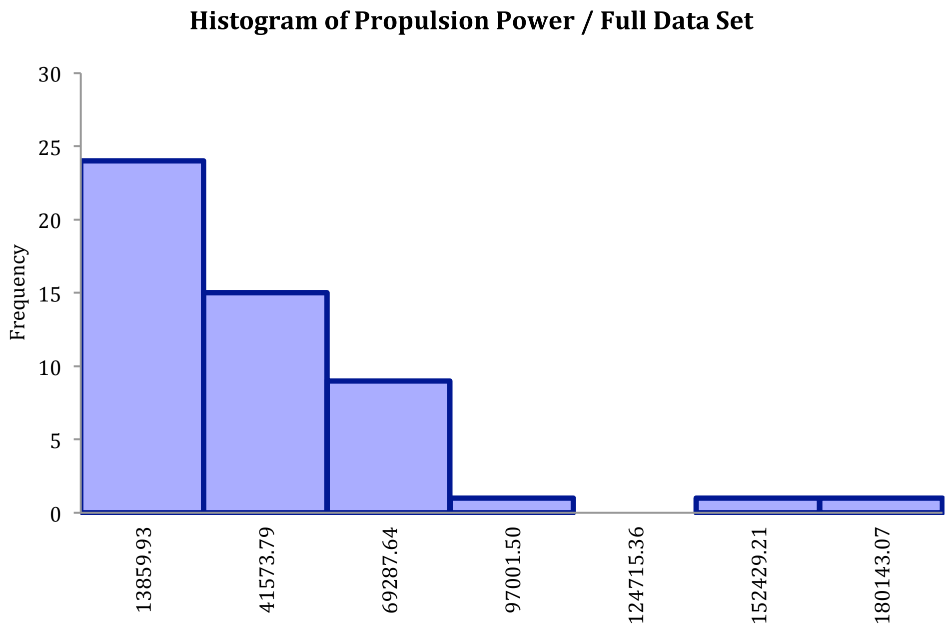

Figure 9: Histogram of Propulsion Power

A series of histograms were also created using StatTools® to example the relative frequency distribution of the sample data collected. Nearly all of the variables show histograms like the one included as Figure 9, which is heavily skewed to the left. The only exception to this was the variable of speed, which appears to resemble a normal distribution roughly symmetric about a vertical axis near the mean value as shown in Figure 10. The complete series of histograms for the naval combatant database is included as part of Appendix B.

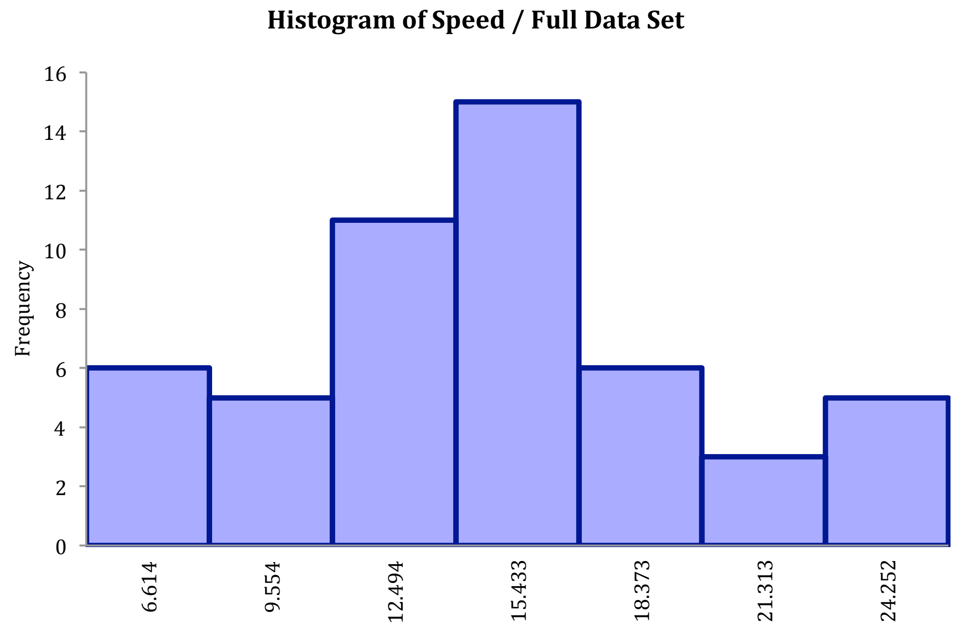

Figure 10: Histogram of Speed

The dataset of 46 vessel classes was separated into two subsets, the first containing 9 electrical transmission ships and the second containing 37 mechanical transmission ships. The variable statistics summaries were rerun on each of these subsets. The results for the mean and range of value are shown below in Table 3. Based on the mean values, electrical ships are newer, heavier and slower than their mechanical counterparts. Additionally they have larger crews and have much higher installed electrical generation capacities. On the surface these results would seem to support the qualitative arguments that electrical propulsion architectures are better suited to ships with high levels of electrical load, however this conclusion requires further investigation in order to be confirmed. It must also be pointed out that this generic analysis is very limited because it is based solely on 9 electrical ships versus 37 mechanical ships, which do not provide a large enough sample size to draw significant conclusions from.

Table 3: Summary of Mean and Range values for Data Subsets

	Mean Values		Range of Values	
	Electrical Ships	Mechanical Ships	Electrical Ships	Mechanical Ships
Class Commissioned	2000	1981	35	76
Vessel Weight	15862211	12041863	45019377	92877864
Speed	10.99	14.65	12.85	20.58
Propulsion Power	30262	39801	67336	193254
Electrical Power	18315	2933	51626	14897
Specific Power	0.144	0.451	0.271	1.416
Range (NM)	7872	5175	12429	15700
Crew Size	730	661	3058	6295

In addition to the observations already noted from the descriptive statistics analysis, the variance of nearly all of the variable categories was larger than the mean value for that category. This fact, combined with the histogram plots, suggests that the broad range of vessels selected for this historical analysis may not accurately represent a normal distribution of the full population. Since reducing the sample size to fewer, more similarly designed ship classes in an attempt to approximate a normal distribution was not deemed viable due to the already low number of historical examples, these statistical issues were addressed by normalizing the data set to each variable's maximum value prior to the Principal Component Analysis step as discussed in a subsequent section.

Multivariable Regression Analysis

Because direct comparison of the parameters on two dimensional plots did not reveal any strong correlations to the propulsion system architecture, linear multivariable regressions were next considered in an attempt to numerically define a relationship between the propulsion system architecture and the available historical data. As part of the NAME 6097 Marine Engineering Process Modeling, Control and Automation course the author received an empirical regression equation, shown as Equation 3.1, to predict the electrical generation capacity of diesel powered merchant ships using independent variables of propulsion power and crew size [22]. The propulsion power is in horsepower, and the resulting value is predicted in kilowatts.

$$P_{Elec} = \left(0.15 * P_{Propulsion}\right) + (1.6 * Crew) + \left(9 * \sqrt{Crew}\right) + 80 \qquad (3.1)$$

While not a linear relationship, it was developed through a regression analysis of empirical data, similar to the approach utilized in this paper. Figure 11 shows a plot of Equation 3.1's predicted values compared to the actual electrical capacities of the naval combatants included in the database. Since the empirical formula used was based on merchant ships, it is unsurprising that Equation 3.1 grossly underestimates the electrical load of naval combatants. However, this equation served as a starting point for the author's investigation into regression analysis of multiple variables to define the relationship between either installed electrical capacity or propulsion transmission architecture and the historical data.

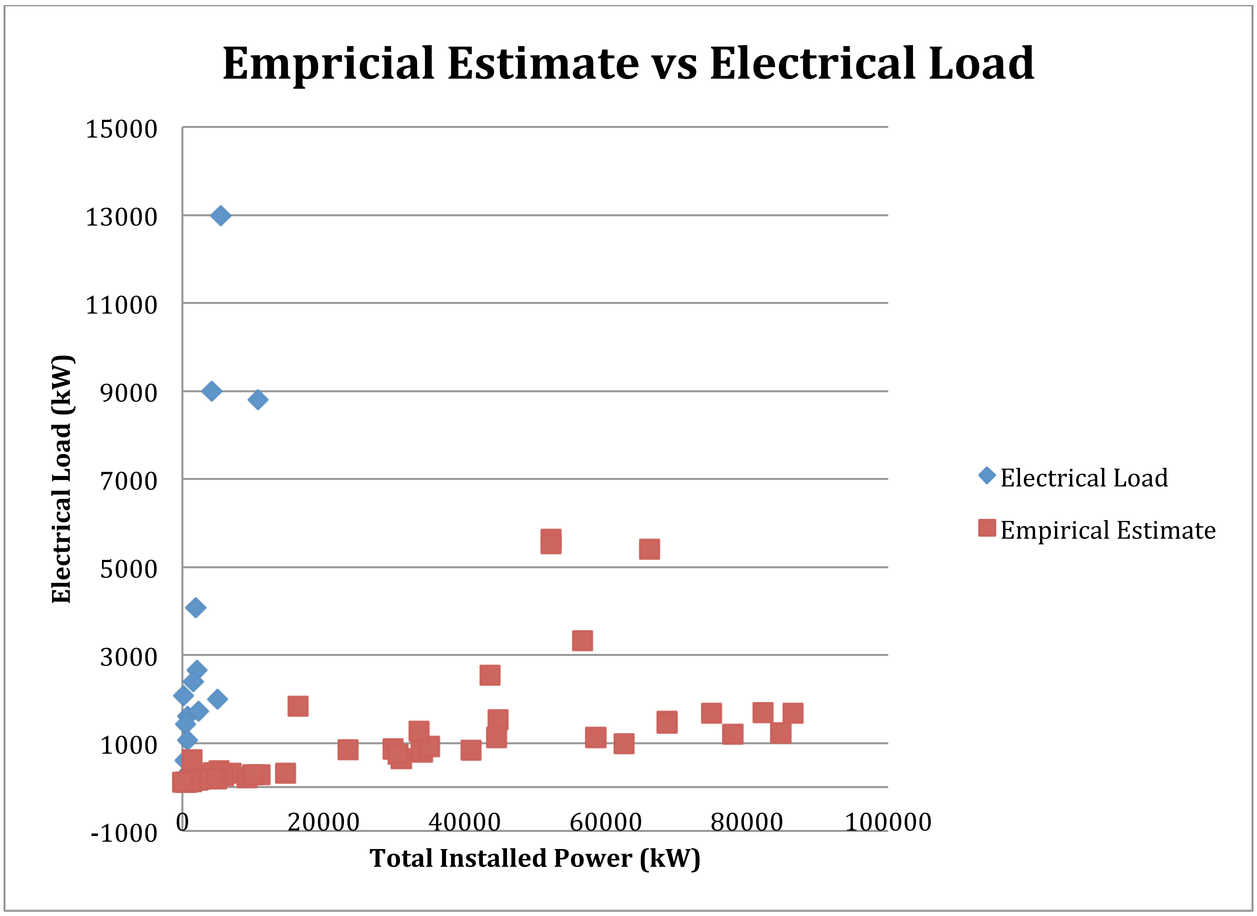

Figure 11: Plot comparing actual vs. empirical predicted values of Electrical Power Capacity

Because several of the parameters listed in Table 2 are ratios or combinations of only a few base characteristic variables, the regressions were only performed using the 7 base variables shown below in Table 4. Since these ratios are by their nature combination of the base variables, they are not truly independent variables. By removing these ratios and other parametric

combinations from the regression analysis process the number of inputs was significantly reduced, decreasing the complexity of the problem without an appreciable loss in accuracy of the predictions.

Table 4: List of the Base Variables Utilized

Base Variables	
Class Commissioned Since	year
Vessel Weight	kg
Speed	m/s
Propulsion Power	kW
Installed Electrical Power	kW
Range	NM
Crew Size	people

Initially these regressions were used to predict a categorical value of 0 or 1 for electrical transmission or mechanical transmission ships using the 7 variables listed in Table 4. However, low R^2 values, near 0.5, led the author to focus instead on using the installed electrical power capacity as the dependent variable. These regressions also yielded relatively low R^2 values when applied to the complete dataset of both electrical and mechanical transmission architecture ships.

Therefore, the database was then separated into two separate subsets, one containing the 9 electrical transmission ships and the other 37 mechanical transmission ships. Regressions performed on these separated subsets yielded similar results, suggesting there is not a strong relationship between the amount of electrical generating capacity for these types of ships and the other 6 base variables listed in Table 4.

Principal Component Analysis

A ship's general characteristics are highly interdependent, and a change in one value, such as an increase in displacement, usually results in a corresponding shift in other characteristics, such as an increase in the amount of propulsion power required to achieve the same speed. The StatTools® software used to perform the linear multivariable regressions of the datasets included a built in assumption that all of the variables used as inputs are independent of each other. A linear

correlation matrix of the database, included as Table 5, shows that most of the variables have at least some interdependency with each other. The covariance values over 0.50 were highlighted to show the stronger correlations.

Table 5: Covariance Table for the 7 Base Variables

	Class Commissioned Since	Vessel Weight	Speed	Propulsion Power	Installed Electrical Power	Range	Crew Size
Class Commissioned Since	1	0.016	-0.025	-0.023	0.383	0.192	0.008
Vessel Weight		1	-0.040	0.757	0.477	0.361	0.969
Speed			1	0.352	-0.108	-0.423	-0.043
Propulsion Power				1	0.230	0.157	0.686
Installed Electrical Power					1	0.167	0.495
Range						1	0.230
Crew Size							1

Due to the large number of supposedly "independent" variables included in the analysis, and the low R^2 values for these regressions, the author determined that a Principal Component Analysis (PCA) was required to determine how many variables were actually needed to define dependent variables of either Installed Electrical Capacity or the categorical variable of the propulsion system architecture being considered. A PCA takes the covariance matrix of the sample data and calculates the Eigen values and Eigen vectors of the matrix. The Eigen vectors are the principal components that describe how the sample data is changing in relation to the other Eigen vectors. In essence, the PCA reorients the sample data onto a new set of axes, defined by the Principal Components, which are orthogonal to each other like the typical X-Y-Z coordinate system. By comparing how much each Eigen vector impacts the total amount of variance of the sample data, the number of dimensions required to describe the sample data space with some reasonable level of accuracy can be determined.

In order to successfully run the PCA on the naval combatant database created, all of the values in the data set had to be normalized to the highest value for each variable. This was done in Microsoft Excel prior to importing the sample data into Matlab. The maximum value of each column was determined from the statistical summary reports, and then each sample point was

divided by the maximum value. So instead of being measured in conventional units, such as kilowatts, each value was converted to a percentage of the ship with the highest value for the category. For the Class Commissioned Since variable, the information first had to be converted to the age of the vessel in the year 2015. The oldest ship included in the dataset was originally commissioned in 1936. So for that variable, every class's age was represented as a percentage of the age of that class of vessels, or 79 years. Next, the average of these new values was subtracted from each data point to adjust the data to have a mean of 0. Not only was this step a requirement for the PCA process, it also resolved the statistical concerns regarding the spread and variance of the sample data by normalizing every category to be between -1 and 1.

Table 6: PCA results predicting transmission type using 12 variables

Principal Component	% Explained by Prin Comp	Total % Explained
1	67.39	67.39
2	13.66	81.05
3	7.06	88.11
4	4.98	93.09
5	2.22	95.31
6	2.08	97.39
7	1.83	99.22
8	0.49	99.71
9	0.17	99.88
10	0.06	99.94
11	0.05	99.99
12	0.01	100.00

The PCA was performed on this normalized sample data using Matlab, and an example of the PCA script utilized for the electrical dataset is included as part of Appendix C. The last column of the dataset was the dependent variable being considered for the PCA. The first PCA run utilized the complete data of 46 ship classes and all 12 numeric variables to describe the dependent categorical variable of Propulsion Transmission type. Table 6 summarizes the PCA results, showing how much each principal component explains the variance of the sample data. In this case, 5 principal components, or dimensions, describe 95% of the sample data variance. The PCA was rerun using the first 5 variables, yielding the results shown in Table 7.

Table 7: PCA results predicting transmission type using only 5 variables

Principal Component	% Explained by Prin Comp	Total % Explained
1	49.44	49.44
2	25.19	74.62
3	20.25	94.88
4	4.57	99.44
5	0.56	100.00

Because the author was unsure if the categorical variable of transmission type could be accurately predicted with a neural network, a PCA was also performed for the dependent numerical variable of Installed Electrical Generation Capacity. The PCA was initially performed on the complete dataset using 11 independent variables. It was then refined using the results shown in Table 8, and the PCA was rerun using 5 variables on 3 data sets: the 9 electrical transmission ships, the 37 mechanical transmission ships, and the full data set containing all 46 vessel classes. The PCA results are summarized in Table 9. Once again, the entire sample data could be defined with over 90% accuracy using only 5 dimensions, and when the refined PCA was run with only 5 variables, the variance of the Installed Electric Power Capacity could be accurately explained with only 3 or 4 of those dimensions.

Table 8: PCA results predicting Electric Power Capacity using 11 variables

Principal Component	% Explained by Prin Comp	Total % Explained
1	42.44	42.44
2	21.39	63.82
3	15.28	79.10
4	6.68	85.78
5	6.38	92.16
6	5.50	97.67
7	1.47	99.14
8	0.52	99.65
9	0.18	99.83
10	0.14	99.97
11	0.03	100.00

Table 9: PCA results predicting Electric Power Capacity using 5 variables

	Full Data Set (Both Types)		Mechanical Transmission		Electrical Transmission	
Principal Component	% Explained by Prin Comp	Total % Explained	% Explained by Prin Comp	Total % Explained	% Explained by Prin Comp	Total % Explained
1	49.44	49.44	46.47	46.47	84.44	84.44
2	25.19	74.62	33.36	79.84	9.62	94.06
3	20.25	94.88	13.30	93.13	5.38	99.44
4	4.57	99.44	6.28	99.42	0.44	99.88
5	0.56	100.00	0.58	100.00	0.12	100.00

The next step was to reattempt the linear multivariable regressions for the dependent variable of Installed Electrical Power, while limiting the number of independent variables to either 3 or 4, as suggested by the results of the PCA. The results of these regressions calculated using StatTools® are summarized in Table 10. Unlike the previous regression attempts, there was a strong correlation (R^2=0.95) for the electrical transmission ships, but there was still only a weak relationship between the mechanical ships. Since there are far more ships in the mechanical category, they appear to have overwhelmed the electrical ship's relationship when the regression was applied to both sets of ships at the same time. The full set of linear regression results are included as part of the StatTools® results in Appendix B.

Table 10: Summary of Linear Regression Results for predicting Electrical Power Capacity

Regression Results for Normalized Data Set								
				Coefficients:				
Data Set	# Ind Var	Multi R	R^2 Value	Constant	Crew	Prop Power	Speed	Age
Both	4	0.6433	0.4139	-1.00E-16	0.739	-0.214	-0.194	-0.357
Both	3	0.5205	0.271	-7.62E-17	0.752	-0.231	-0.023	-
Electrical	4	0.9755	0.9516	0.154	2.368	-1.762	1.508	-0.794
Electrical	3	0.956	0.914	0.302	2.334	-0.882	1.16	-
Mechanical	4	0.6443	0.4151	-0.053	0.172	0.093	-0.042	-0.087
Mechanical	3	0.5938	0.3526	-0.057	0.161	0.092	-0.025	-

The regression analysis preformed with the reduced number of variables, as suggested by the results of the PCA, indicates that is it possible to predict most of an electric drive ship's electrical generation capacity if you know the preliminary variables of Crew Size (persons), Propulsion Power (kW), Speed (m/s), and class age (years). The high R^2 values of the two regression equations suggest that over 95% of the variance of the electrical generation capacity is explained by the equations using only 3 or 4 of the variables. This particular relationship is discussed more in the conclusions section.

Neural Networks

Since a linear regression analysis did not reveal any strong relationships to the categorical variable defining the propulsion transmission architecture, the author next attempted to create neural networks to predict the dependent variables. A neural network contains a series of "hidden" neurons or nodes that perform simple calculations on weighted sums of inputs from the previous layer of nodes. The neural networks constructed for this problem contained four layers, two of which are hidden. The first layer is the input node where the sample data is entered. The second layer, which is the first hidden layer, contains the activation function. There is another hidden layer that processes the output from the first hidden one, then a final layer of nodes that provides the output of the neural network. A simple depiction of the type of neural network used for this analysis is shown in Figure 4 earlier in this document.

Initially, the NeuralNet® feature of DecisionTools® suite was used to construct the neural networks. However, when the NeuralNet® network was used to analyze the dependent variable of Installed Electric Power, the results returned were nearly identical to the multivariable linear regression. Upon further investigation, the author discovered that the NeuralNet® program was limited to a linear analysis of the data provided to it, which defeated the purpose of using a neural network in this case. NeuralNet® also allowed for a categorical dependent variable, but as with the Installed Electric Power network, the activation function was limited to a linear function, and was unable to predict the system architecture with any more accuracy than the linear multivariable regressions.

So instead of the linearly limited NeuralNet® program, the neural network analysis was performed in Matlab, which allowed for a non-linear activation function in the first level of hidden nodes. Based on the structure of the normalized dataset being supplied to the neural network, Matlab's default activation function, the TanSig function, was selected as the activation function since the range of the entire normalized input matrix was between -1 and 1.

Several different neural networks were configured and trained in an attempt to find an ideal prediction model for which type of propulsion transmission architecture was used on a given class of ships. The networks were each trained for up to 1000 iterations until the performance criteria was satisfied, the gradient of improvement fell below 7.5×10^{-5}, or a time period of two hours elapsed. All of the networks converged prior to the two hour time limit, and most of them had their training stopped by either the performance criteria or the improvement gradient. Once the network was trained and tested, the resulting weight and constant matrices for each hidden layer

were retrieved in order to preserve the trained neural network. These matrices are included in their entirety as part of the collection of Matlab results contained in Appendix C.

Table 11: List of Neural Network Configurations and Training Results

Neural Net	NN-1	NN-2	NN-3	NN-4	NN-5	NN-6	Pattern Rec
# Independent Var	3	3	3	6	4	4	4
Dependent Var	Transmission	Transmission	Elec Power	Transmission	Transmission	Elec Power	Transmission
Training Epochs (iterations)	1063	8262	10000	144	2640	1485	8
Time (sec)	11	82	97	1	26	14	0
Performance	6.05E-05	3.55E-02	6.57E-04	7.25E-05	7.49E-05	7.49E-05	0.0593
Gradient	3.19E-02	1.00E-07	7.33E-05	2.22E-03	4.34E-03	2.02E-03	0.0229
Mu	1.00E-08	1.00E-05	1.00E-08	1.00E-06	1.00E-07	1.00E-07	
Normalized Independent Var:							
Crew Size	X	X	X	X	X	X	X
Propulsion Power	X	X	X	X	X	X	X
Speed		X	X	X	X	X	X
Age				X		X	
Heaviest				X			
Electrical Power	X			X	X		X

There were 6 different neural networks developed using variations of the script included as Appendix C. Each of these networks combined a different set of independent variables to predict either the transmission method or the installed electric power capacity. A seventh network was developed using the Pattern Recognition Network wizard built into Matlab 2013. This final network was selected as a means to verify the method used to create the categorical variable of transmission architecture. However the limitations of the built in wizard did not allow for performance metrics consistent with those of the other neural networks. Table 11 combines the network configurations and their respective results.

The network identified as NN-4 was included to show that the additional independent variables did not have a significant impact on the end result of the neural network's ability to predict the transmission architecture. Even though NN-4 required far less iterations to train, the performance and gradient metrics were very similar to the other neural networks, verifying the PCA results.

Conclusions

The author's attempt to identify the likely propulsion system architecture using a combination of design parameters known early in the design process was only successful when a neural network was trained and tested against the original database. While this establishes that a numerical relationship does in fact exist between the tested parameters and the propulsion system architecture, the neural network does not provide an easily identifiable equation or prediction method that enables others to predict which propulsion system architecture should be used in new naval combatant designs without access to the original database of ship parameters.

There are many possible reasons for why the author was unable to find a simpler prediction method for the propulsion system architecture. Many of the approaches used in this paper were limited to linear relationships, and further research into the subject may reveal non-linear relationships that better describe the relationship between the propulsion system architecture and the selected ship parameters. In addition, there are only a relatively small number of naval combatant ship classes to include in the database, and even fewer of those samples are electric drive ships. Future research could expand the database to include naval ships from other nations if their relevant parameters can be found or reliably estimated. This would increase the statistical reliability of the results, and also possibly enable the discovery of numerical relationships that could not be established with the limited number of samples obtained for this thesis.

The database collected also contains classes of ships that were designed and built as early as the 1930's. Many of the technologies used on those ships have gone through countless generational changes in the decades since. The average electrical loading condition of a ship built in modern times is several orders of magnitude larger than those that were built for the World War II era Navy. The author included these older ships in an attempt to increase the robustness of the database by increasing the number of samples; however their inclusion may have negatively impacted the analysis. Until more classes of ships are built with modern technologies and their respective higher electrical loads, there are not enough samples to include for a robust analysis without including these older ship designs.

Besides the statistical and numeric limitations of this thesis, there may be alternative explanations for why a simple parametric relationship could not be established. The construction of a new class of ships for a government agency, such as the US Navy or US Coast Guard, can sometimes be heavily influenced by politics rather design requirements and ship parameters. The choice of which government contractor designs or builds a class of ship can influence the

complexity of the propulsion system selected, especially if the contractor does not have experience with electric drive ship designs. Additionally, the technological maturity of naval electric drive systems has only recently reached levels where it is being considered in the design process. Perhaps once the concepts of IFEP and IPS are proven on the DDG-1000 class electrical propulsion architectures will become more commonplace and this analysis can be revisited.

The author's collection of ship parameters also did not include the actual electrical load conditions for each ship class. As discussed elsewhere, the installed electrical generation capacity was substituted since more information was publicly available. One of the major selling points of integrated electric propulsion architectures is the large amount of excess power that can be available for non-propulsion electrical loads. This is a qualitative feature of integrated electric ships that may not be accurately reflected in the quantitative approach selected in this paper. In addition, it is a design feature that will likely increase in importance as newer high-energy combat systems reach their design maturity, such as the electromagnetic rail guns and catapults.

A similar approach to the one discussed in this paper might have better success if applied to a different database with a higher number of samples, such as cruise ships. While subject to dramatically different requirements than a naval warship, this approach could be used to prove the theory behind the approach until such time that there are enough examples of electric drive naval vessels. In addition, it might have been more beneficial to separate the ships into different groups, traditional electrical distribution systems and integrated electric distribution systems. The integrated ships have a much higher electrical generation capacity, which may have served to single them out when analyzed.

Despite the shortcomings of this thesis, there were several beneficial discoveries revealed as side effects of this investigation. The principal component analyses show that the propulsion architecture relationship can be accurately defined by as few as 4 dimensions. Since PCA does not define those dimensions as an output, such as the regression's output of an equation, the exact nature of those dimensions remain unknown. However, the results of the PCA do allow the problem to be approached in future research with a limited number of inputs without excessively sacrificing the overall reliability or accuracy of the analysis, which is displayed by the ability of the neural networks to establish a repeatable relationship between the reduced number of independent variables and the transmission type for each class of ship.

The author was also able to generate a reliable prediction model for the installed electrical power generation capacity of an electric drive naval combatant using multivariable linear regression. As originally presented in Table 9, this equation uses a normalized set of input values to predict a naval vessel's electrical capacity. Since the relationship holds true for the normalized values, the coefficients can be adjusted to reflect the actual ship parameters without the additional step of normalizing the variables. The author ran an identical regression analysis using the actual ship parameters instead of the normalized data. This yielded Equation 4.1 where P_{Elec} and $P_{Propulsion}$ are both in kilowatts (kW), N_{Crew} is the size of the ship's crew in persons, and V_{Ship} is the vessel's speed in m/s. Equation 4.1 has identical performance metrics to the normalized regression results presented in Table 9 with the same variables, but has updated coefficients.

$$P_{Elec\ Installed} = (19.34 * N_{Crew}) - \left(0.24 * P_{Propulsion}\right) + \left(2354.16 * V_{Ship}\right) - 14512.1 \qquad (4.1)$$

Equation 4.1 was used to calculate a predicted value for each of the 9 electric drive ship classes, and these predicted results were compared to the actual values for each class of ship that utilizes an electrical propulsion system architecture. The classes were organized in increasing size of the original value to simplify the presentation of the differences in actual and predicted values. The equation appears to be more accurate for ships with higher levels of electrical capacity. It should be noted that despite the high R^2 value of this regression equation, it is only based on 9 observations whose sample data points do not appear to be not normally distributed. Further research using additional electric drive ships is required in order to confirm the validity of this prediction equation.

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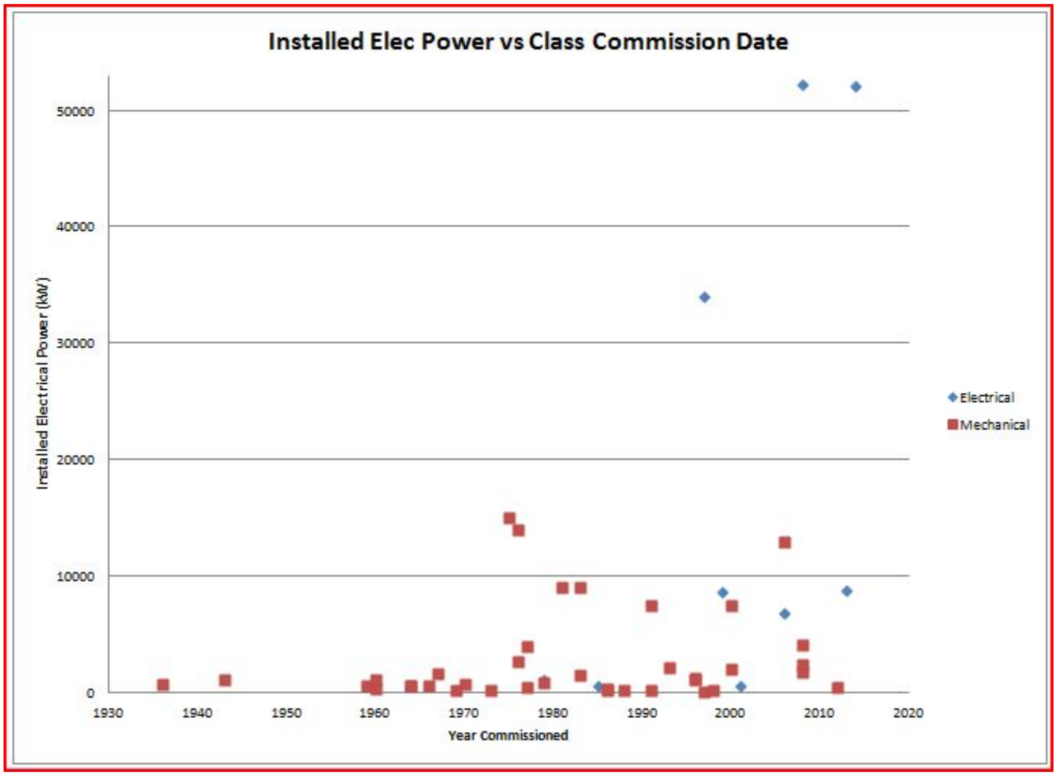
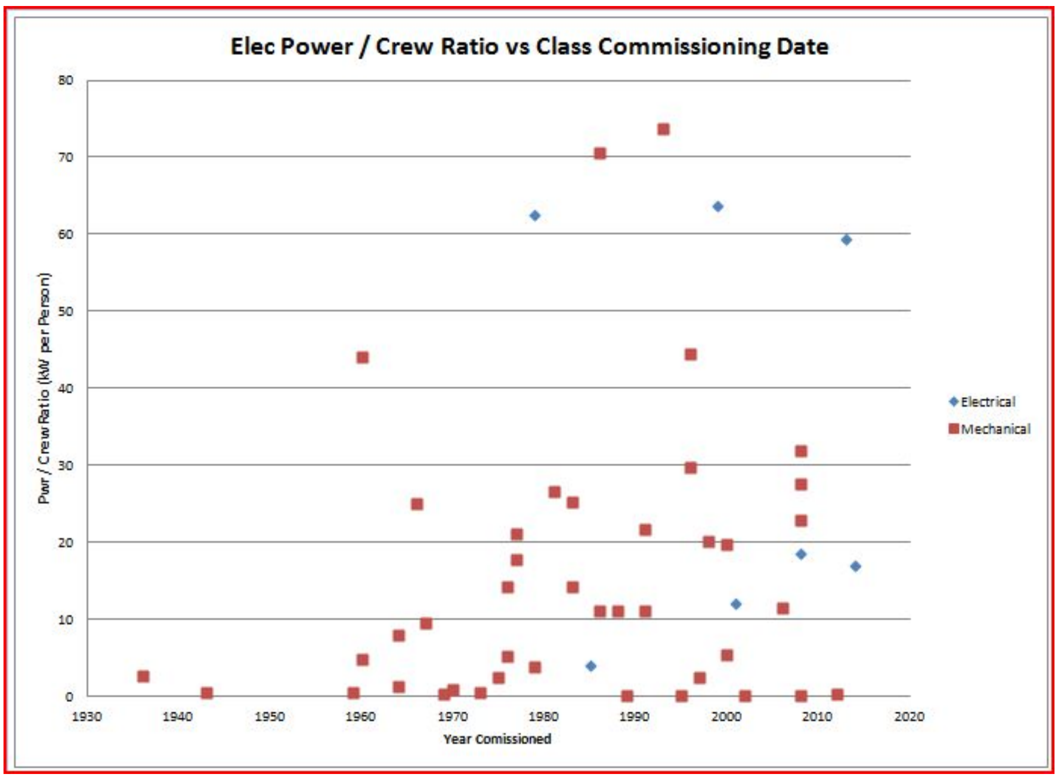
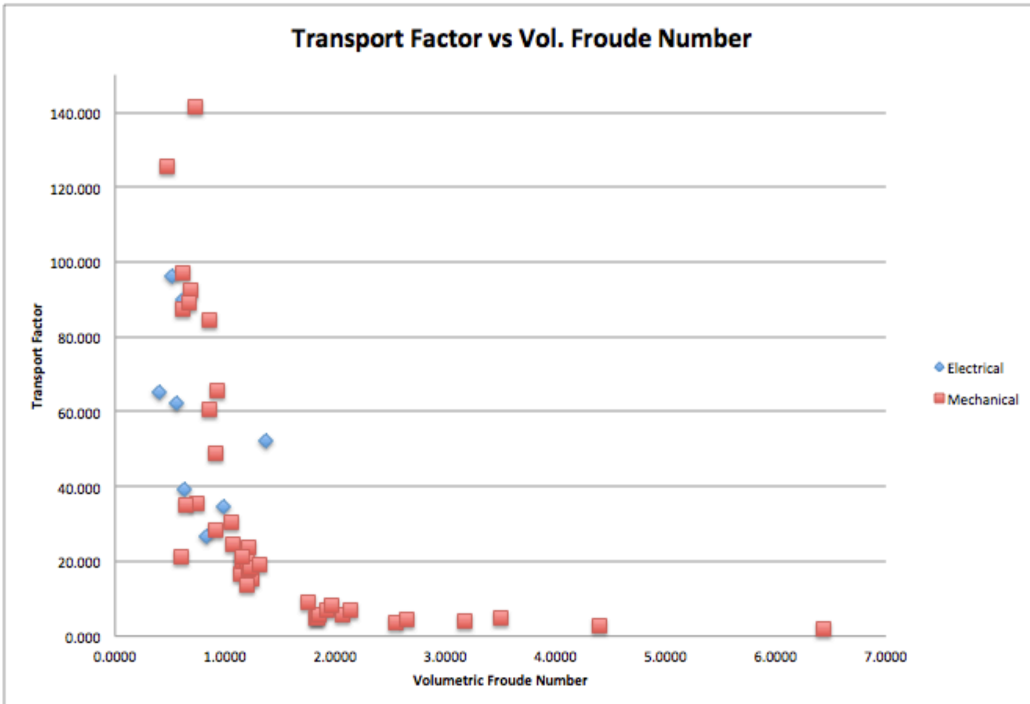
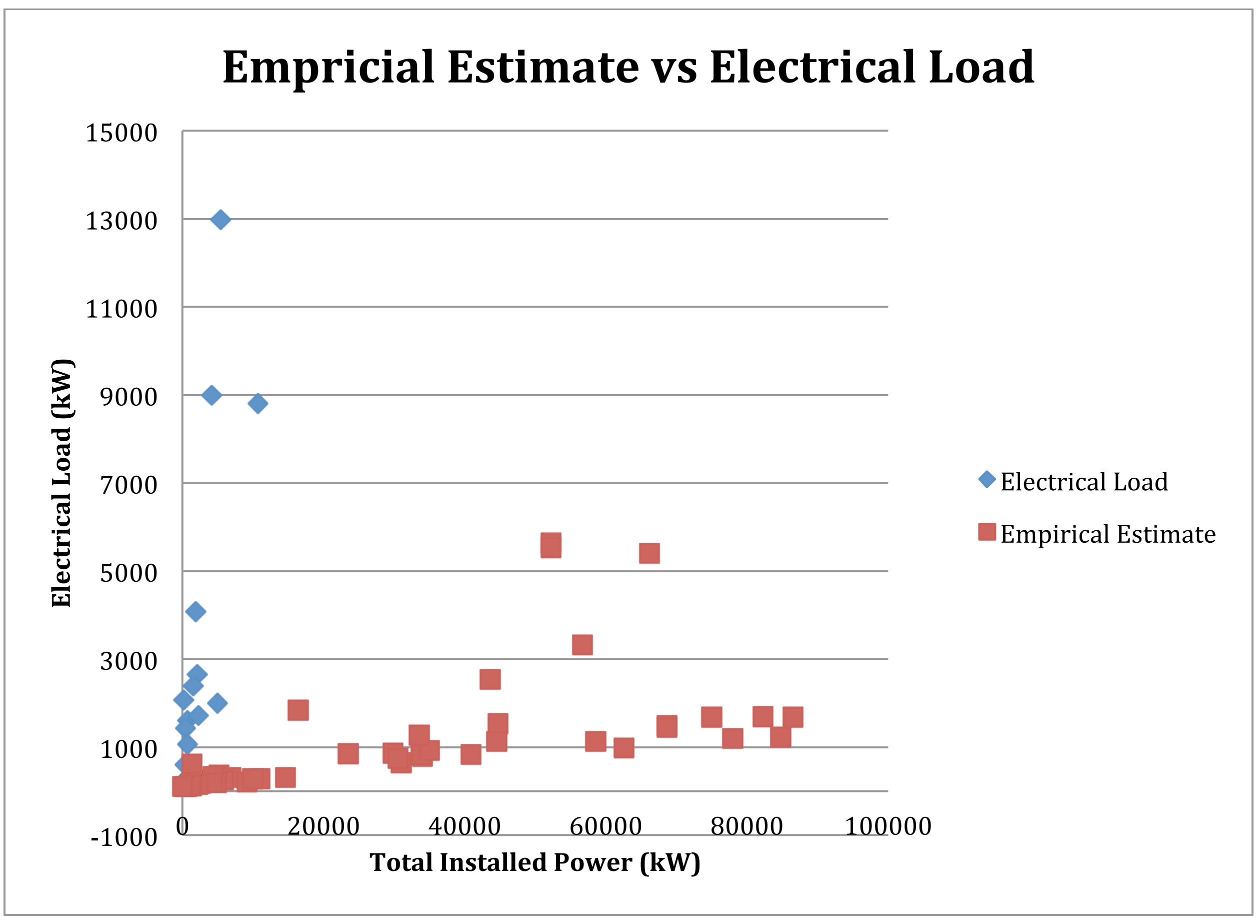
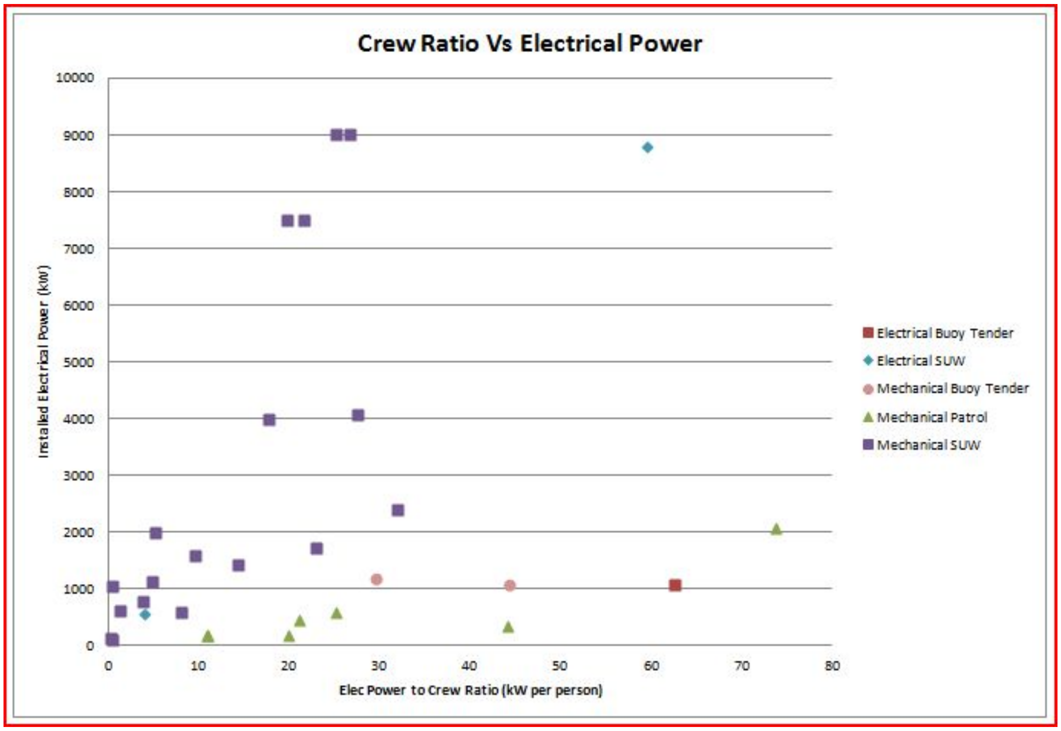
Appendix A – Variable Comparisons Using Two Dimensional Plots

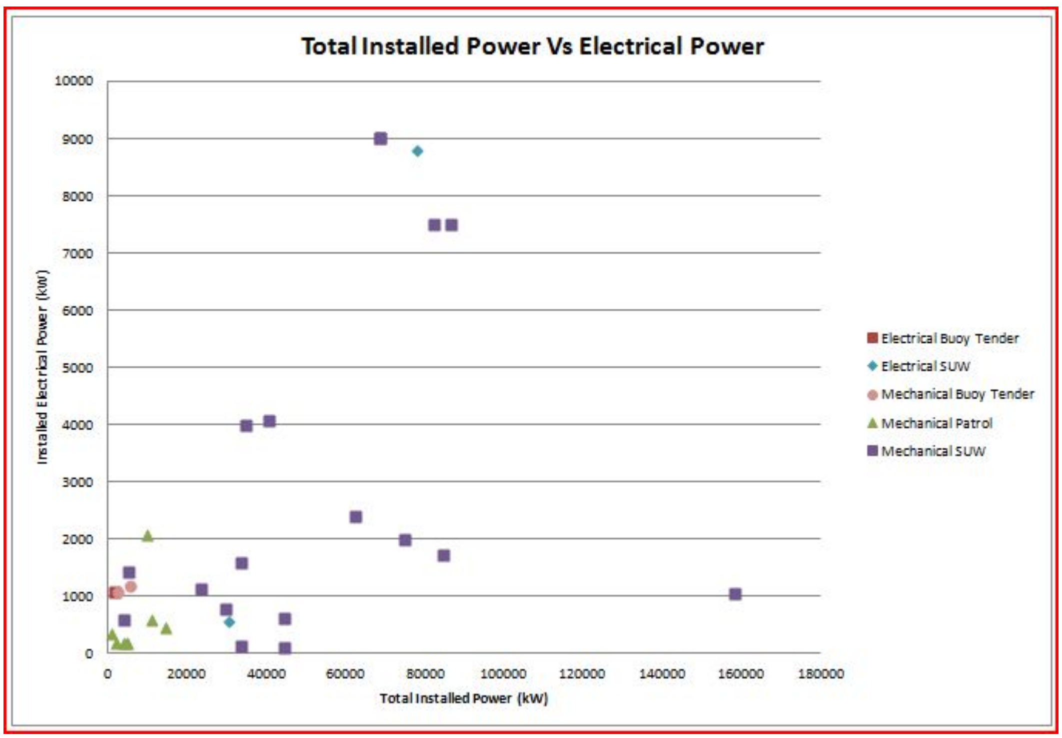


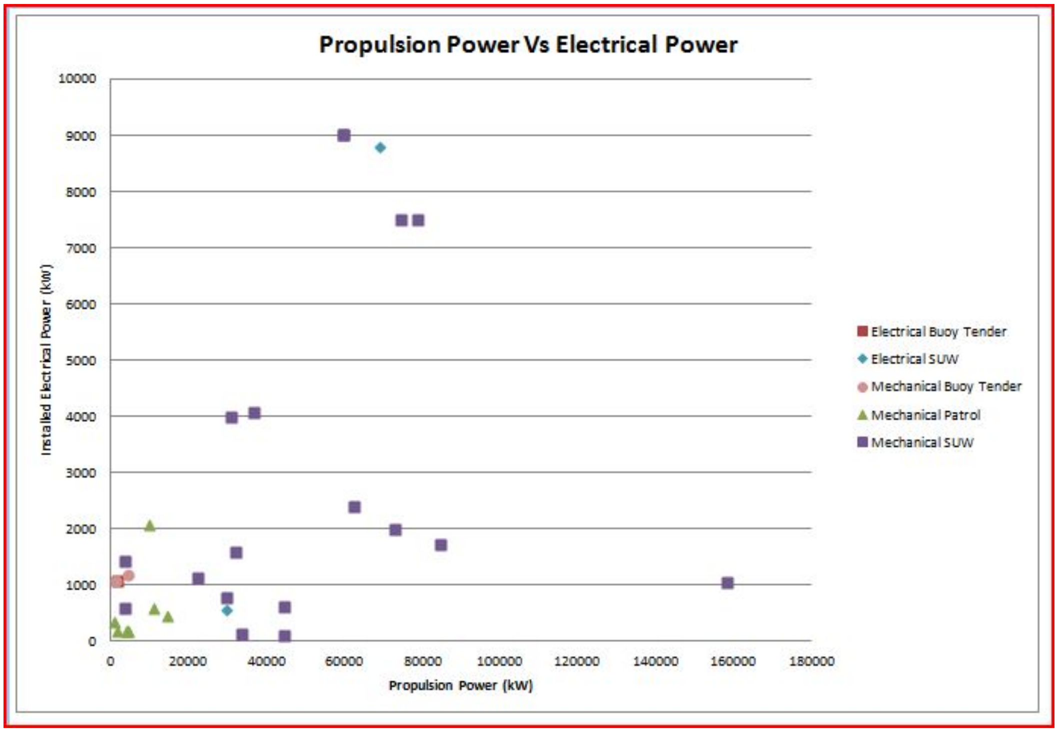


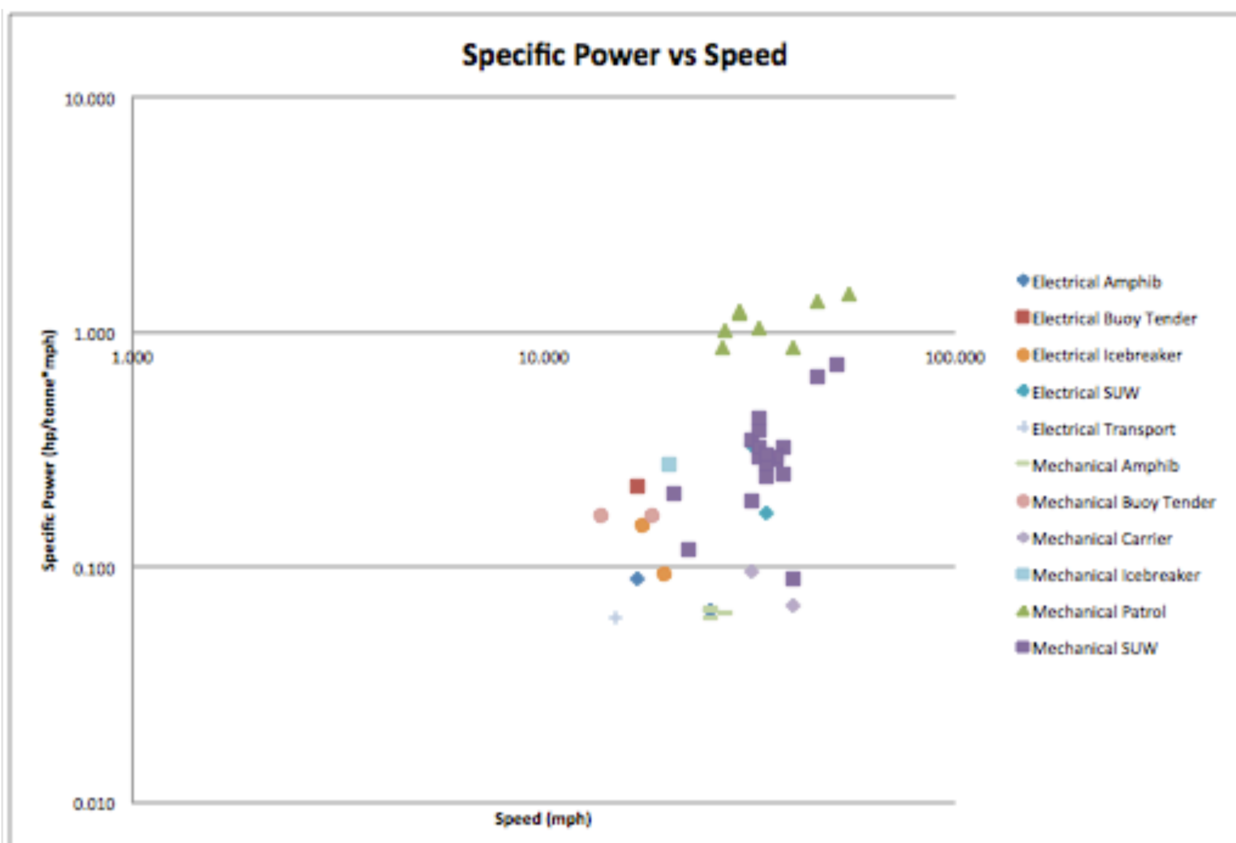

Transport Factor vs Vol. Froude Number
Transport Factor
140.000
120.000
100.000
80.000
60.000
40.000
20.000
0.000
0.0000
1.0000
2.0000
3.0000
4.0000
5.0000
6.0000
7.0000
Volumetric Froude Number
Electrical
Mechanical

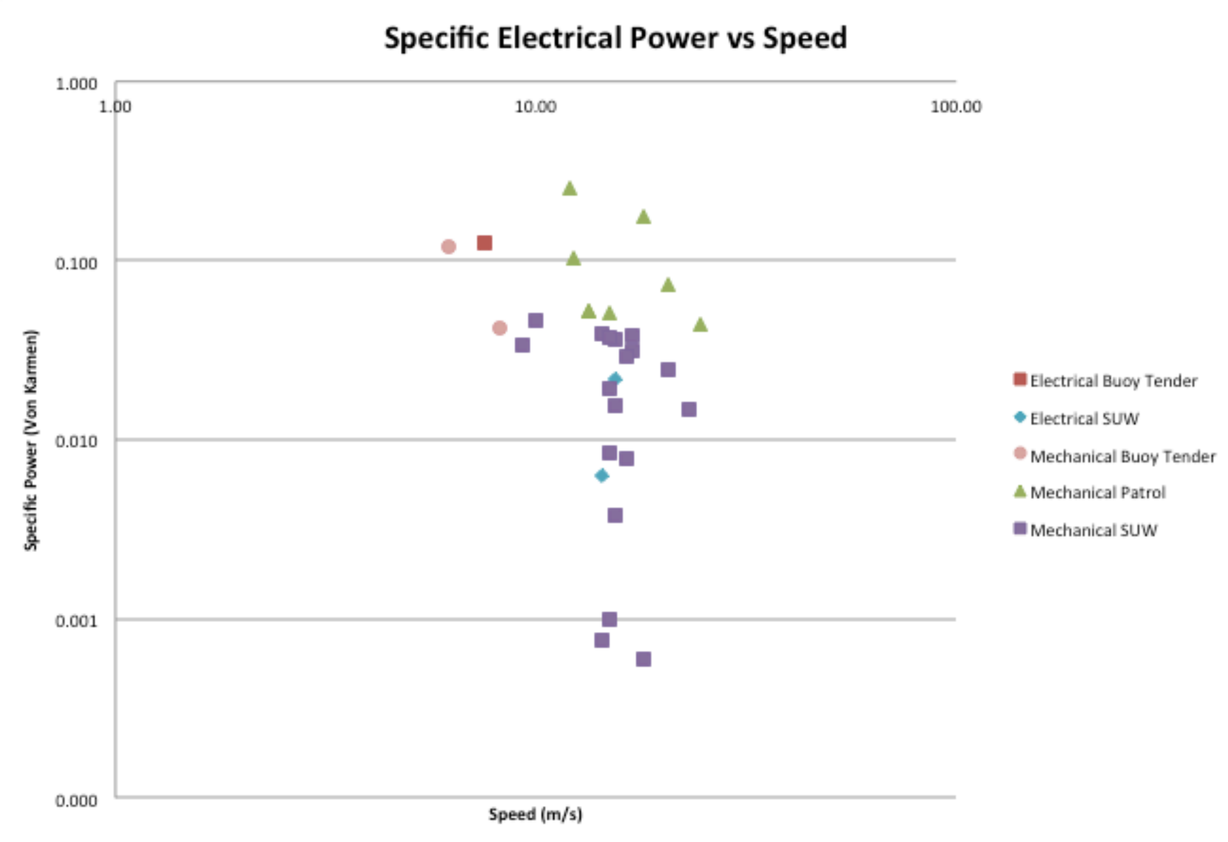

Empricial Estimate vs Electrical Load
Electrical Load (kW)
15000
13000
11000
9000
7000
5000
3000
1000
-1000
0
20000
40000
60000
80000
100000
Total Installed Power (kW)
Electrical Load
Empirical Estimate


Crew Ratio Vs Electrical Power
Installed Electrical Power (kW)
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
0
10
20
30
40
50
60
70
80
Elec Power to Crew Ratio (kW per person)
Electrical Buoy Tender
Electrical SUW
Mechanical Buoy Tender
Mechanical Patrol
Mechanical SUW


Total Installed Power Vs Electrical Power
Installed Electrical Power (kW)
10000
9000
8000
7000
6000
5000
4000
3000
2000
1000
0
0
20000
40000
60000
80000
100000
120000
140000
160000
180000
Total Installed Power (kW)
Electrical Buoy Tender
Electrical SUW
Mechanical Buoy Tender
Mechanical Patrol
Mechanical SUW


Propulsion Power Vs Electrical Power
Installed Electrical Power (kW)
Propulsion Power (kW)
0
1000
2000
3000
4000
5000
6000
7000
8000
9000
10000
20000
40000
60000
80000
100000
120000
140000
160000
180000
Electrical Buoy Tender
Electrical SUW
Mechanical Buoy Tender
Mechanical Patrol
Mechanical SUW


Specific Power vs Speed
Specific Power (hp/tonne*mph)
Speed (mph)
10.000
1.000
0.100
0.010
1.000
10.000
100.000
Electrical Amphib
Electrical Buoy Tender
Electrical Icebreaker
Electrical SUW
Electrical Transport
Mechanical Amphib
Mechanical Buoy Tender
Mechanical Carrier
Mechanical Icebreaker
Mechanical Patrol
Mechanical SUW


Specific Electrical Power vs Speed
1.000
1.00
10.00
100.00
0.100
0.010
0.001
0.000
Specific Power (Von Karmen)
Speed (m/s)
Electrical Buoy Tender
Electrical SUW
Mechanical Buoy Tender
Mechanical Patrol
Mechanical SUW

Appendix B – StatTools Reports: Statistical Summaries, Regression Results, and Neural Network Results

StatTools Report

Analysis: One Variable Summary
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Live

One Variable Summary	Class Commissioned Since Data Set #2	Vessel Weight Data Set #2	Speed Data Set #2	Total Installed Power Data Set #2	Propulsion Power Data Set #2	Installed Electrical Power Data Set #2	Transport Factor (Prop Power) Data Set #2
Mean	1985.02	12773418.64	13.954	42622.38	37974.23	5942.83	38.80
Variance	342.20	363941990238227.00	22.319	1838955009.02	1506669186.11	135734723.79	1254.59
Std. Dev.	18.50	19077263.70	4.724	42883.04	38815.84	11650.52	35.42
Skewness	-0.4718	2.3586	0.3636	1.7431	2.0369	3.1895	1.1755
Median	1986.00	4267397.02	14.404	33800.00	31000.00	1140.00	23.54
Minimum	1936.00	68075.14	5.144	1193.12	745.70	102.66	4.03
Maximum	2014.00	92945939.00	25.722	209000.00	194000.00	52199.99	141.29
Range	78.00	92877863.86	20.578	207806.88	193254.30	52097.33	137.26
Count	47	47	47	47	47	46	47
1st Quartile	1973.00	1158293.48	11.318	5808.34	4623.34	576.43	13.70
3rd Quartile	2000.00	15731000.00	16.460	66198.99	55927.49	7500.00	62.35

One Variable Summary	Specific Power Data Set #2	Specific Electrical Power Data Set #2	Vol. Fr. # Data Set #2	Range Data Set #2	Electrical Load Data Set #2	Crew Size Data Set #2	Elec Pwr/Crew Ratio Data Set #2
Mean	0.3922	0.04535	1.2202	5654.24	2961.25	674.66	26.50
Variance	0.1631	0.00273	0.4647	15587007.50	16516229.74	1506007.66	1663.46
Std. Dev.	0.4039	0.05221	0.6817	3948.04	4064.02	1227.20	40.79
Skewness	1.3913	2.1175	1.5518	0.8651	1.9679	2.7904	3.7336
Median	0.2498	0.03353	1.1449	4500.00	1530.64	167.00	14.25
Minimum	0.0416	0.00000	0.4064	300.00	87.77	5.00	0.00
Maximum	1.4575	0.25669	3.5036	16000.00	14483.63	6300.00	242.86
Range	1.4159	0.25669	3.0972	15700.00	14395.86	6295.00	242.86
Count	47	47	47	45	17	47	47
1st Quartile	0.0943	0.00842	0.6788	3000.00	357.50	40.00	4.01
3rd Quartile	0.4294	0.05199	1.3695	7800.00	4191.40	397.00	27.57

StatTools Report

Analysis: Correlation and Covariance
Performed By: Brian Waller
Date: Thursday, March 26, 2015
Updating: Live

Linear Correlation Table	**Class Commissioned Since** Data Set #2	**Vessel Weight** Data Set #2	**Speed** Data Set #2	**Propulsion Power** Data Set #2	**Installed Electrical Power** Data Set #2	**Range** Data Set #2	**Crew Size** Data Set #2
Class Commissioned Since	1.000	0.016	-0.025	-0.023	0.383	0.192	0.008
Vessel Weight	0.016	1.000	-0.040	0.757	0.477	0.361	0.969
Speed	-0.025	-0.040	1.000	0.352	-0.108	-0.423	-0.043
Propulsion Power	-0.023	0.757	0.352	1.000	0.230	0.157	0.686
Installed Electrical Power	0.383	0.477	-0.108	0.230	1.000	0.167	0.495
Range	0.192	0.361	-0.423	0.157	0.167	1.000	0.230
Crew Size	0.008	0.969	-0.043	0.686	0.495	0.230	1.000

StatTools Report

Analysis: Correlation and Covariance
Performed By: Brian Waller
Date: Thursday, March 26, 2015
Updating: Live

Linear Correlation Table	Vessel Weight Data Set #2	Speed Data Set #2	Total Installed Power Data Set #2	Propulsion Power Data Set #2	Installed Electrical Power Data Set #2	Transport Factor (Prop Power) Data Set #2	Speed (mph) Data Set #2	Specific Power Data Set #2	Specific Electrical Power Data Set #2	Vol. Fr. # Data Set #2	Range Data Set #2	Crew Size Data Set #2	Elec Pwr/Crew Ratio Data Set #2
Vessel Weight	1.000	-0.040	0.811	0.757	0.477	0.603	-0.040	-0.457	-0.285	-0.418	0.361	0.969	-0.198
Speed	-0.040	1.000	0.271	0.352	-0.108	-0.469	1.000	0.540	-0.155	0.769	-0.423	-0.043	0.123
Total Installed Power	0.811	0.271	1.000	0.969	0.438	0.240	0.271	-0.366	-0.370	-0.266	0.191	0.755	-0.183
Propulsion Power	0.757	0.352	0.969	1.000	0.230	0.179	0.352	-0.326	-0.423	-0.206	0.157	0.686	-0.182
Installed Electrical Power	0.477	-0.108	0.438	0.230	1.000	0.331	-0.108	-0.318	0.151	-0.293	0.167	0.495	0.300
Transport Factor (Prop Power)	0.603	-0.469	0.240	0.179	0.331	1.000	-0.469	-0.667	-0.257	-0.650	0.550	0.567	-0.114
Speed (mph)	-0.040	1.000	0.271	0.352	-0.108	-0.469	1.000	0.540	-0.155	0.769	-0.423	-0.043	0.123
Specific Power	-0.457	0.540	-0.366	-0.326	-0.318	-0.667	0.540	1.000	0.296	0.915	-0.632	-0.391	0.015
Specific Electrical Power	-0.285	-0.155	-0.370	-0.423	0.151	-0.257	-0.155	0.296	1.000	0.232	-0.389	-0.240	0.538
Vol. Fr. #	-0.418	0.769	-0.266	-0.206	-0.293	-0.650	0.769	0.915	0.232	1.000	-0.627	-0.364	0.141
Range	0.361	-0.423	0.191	0.157	0.167	0.550	-0.423	-0.632	-0.389	-0.627	1.000	0.230	-0.146
Crew Size	0.969	-0.043	0.755	0.686	0.495	0.567	-0.043	-0.391	-0.240	-0.364	0.230	1.000	-0.246
Elec Pwr/Crew Ratio	-0.198	0.123	-0.183	-0.182	0.300	-0.114	0.123	0.015	0.538	0.141	-0.146	-0.246	1.000

Covariance Table	Vessel Weight Data Set #2	Speed Data Set #2	Total Installed Power Data Set #2	Propulsion Power Data Set #2	Installed Electrical Power Data Set #2	Transport Factor (Prop Power) Data Set #2	Speed (mph) Data Set #2	Specific Power Data Set #2	Specific Electrical Power Data Set #2	Vol. Fr. # Data Set #2	Range Data Set #2	Crew Size Data Set #2	Elec Pwr/Crew Ratio Data Set #2
Vessel Weight	363941990238227.00000	###########	##################	###############	104466762457.27100	407623688.22632	###########	###########	-283752.33658	###########	#############	############	-153913839.62986
Speed	-3617022.52453	22.31896	54816.38957	64492.27628	-5981.82709	-78.42187	49.92618	1.03051	-0.03814	2.47549	-7862.68816	-247.37845	23.62419
Total Installed Power	663655184252.70100	54816.38957	1838955009.01635	1613076670.46299	220941693.10403	364028.86239	122620.97449	-6346.87762	-829.09556	-7787.69280	27025096.83133	############	-319380.12756
Propulsion Power	560250532515.35000	64492.27628	1613076670.46299	1506669186.11163	105101201.62735	245630.88587	144265.35251	-5113.66987	-856.78851	-5449.57918	19646501.36018	############	-287703.69663
Installed Electrical Power	104466762457.27100	-5981.82709	220941693.10403	105101201.62735	135734723.79146	135214.91198	-13380.98830	-1502.34272	91.91800	-2330.75193	7257010.56889	6911948.82875	143460.73861
Transport Factor (Prop Power)	407623688.22632	-78.42187	364028.86239	245630.88587	135214.91198	1254.58818	-175.42502	-9.53835	-0.47439	-15.69932	77066.41271	24625.30397	-164.46405
Speed (mph)	-8091062.36601	49.92618	122620.97449	144265.35251	-13380.98830	-175.42502	111.68187	2.30519	-0.08532	5.53753	-17588.36165	-553.37076	52.84589
Specific Power	-3522236.61482	1.03051	-6346.87762	-5113.66987	-1502.34272	-9.53835	2.30519	0.16314	0.00623	0.25203	-1017.34009	-193.92954	0.25307
Specific Electrical Power	-283752.33658	-0.03814	-829.09556	-856.78851	91.91800	-0.47439	-0.08532	0.00623	0.00273	0.00824	-80.05891	-15.38286	1.14610
Vol. Fr. #	-5438203.88003	2.47549	-7787.69280	-5449.57918	-2330.75193	-15.69932	5.53753	0.25203	0.00824	0.46467	-1718.29967	-304.86708	3.91594
Range	21662038390.32440	-7862.68816	27025096.83133	19646501.36018	7257010.56889	77066.41271	-17588.36165	-1017.34009	-80.05891	-1718.29967	15587007.50115	830979.38156	-14612.37003
Crew Size	22674226226.30980	-247.37845	39728129.54281	32682028.45573	6911948.82875	24625.30397	-553.37076	-193.92954	-15.38286	-304.86708	830979.38156	1506007.66420	-12327.52296
Elec Pwr/Crew Ratio	-153913839.62986	23.62419	-319380.12756	-287703.69663	143460.73861	-164.46405	52.84589	0.25307	1.14610	3.91594	-14612.37003	-12327.52296	1663.45617

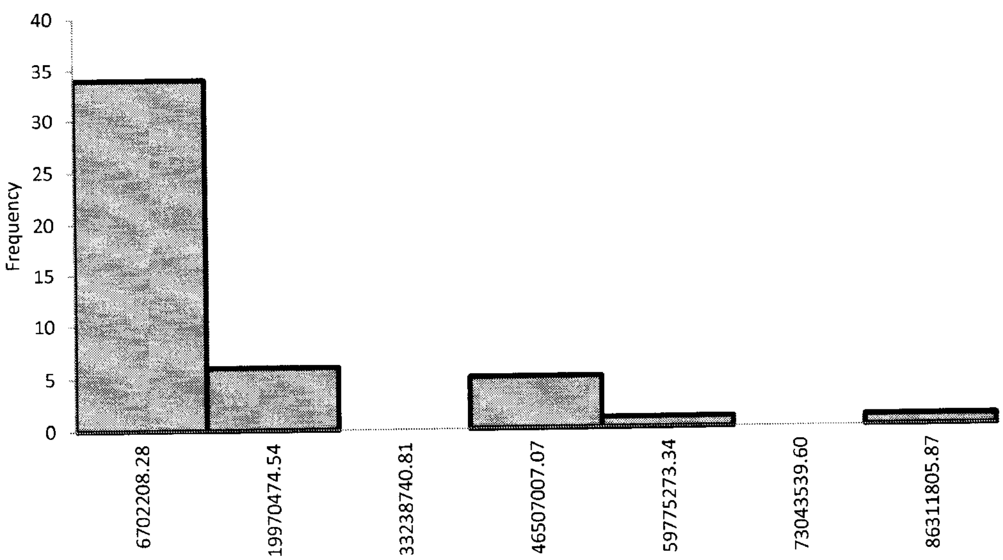
StatTools Report

Analysis: Histogram
Performed By: Brian Waller
Date: Thursday, March 26, 2015
Updating: Live

Vessel Weight / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	68075.14	13336341.41	6702208.28	34	0.7234	5.5E-08
Bin #2	13336341.41	26604607.67	19970474.54	6	0.1277	9.6E-09
Bin #3	26604607.67	39872873.94	33238740.81	0	0.0000	0.0E+00
Bin #4	39872873.94	53141140.20	46507007.07	5	0.1064	8.0E-09
Bin #5	53141140.20	66409406.47	59775273.34	1	0.0213	1.6E-09
Bin #6	66409406.47	79677672.73	73043539.60	0	0.0000	0.0E+00
Bin #7	79677672.73	92945939.00	86311805.87	1	0.0213	1.6E-09

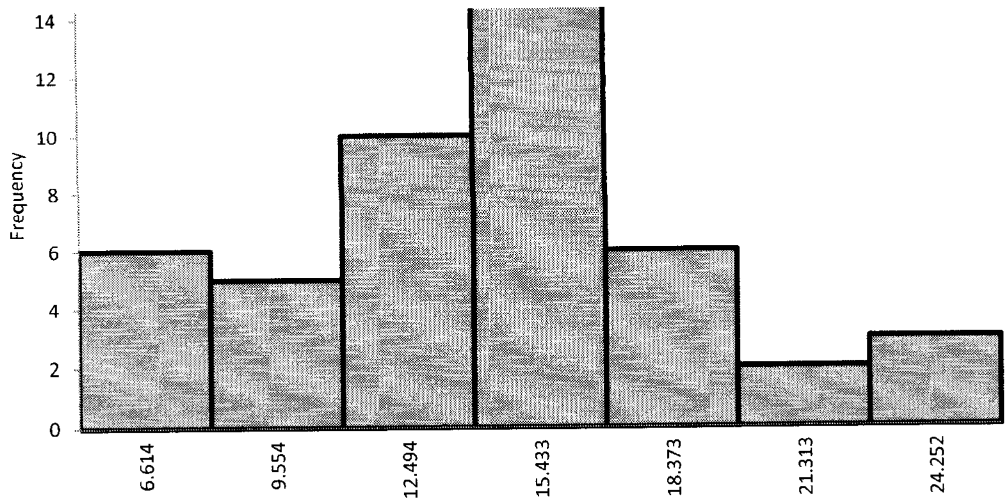
Histogram of Vessel Weight / Data Set #2



Speed / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	5.144	8.084	6.614	6	0.1277	0.043
Bin #2	8.084	11.024	9.554	5	0.1064	0.036
Bin #3	11.024	13.963	12.494	10	0.2128	0.072
Bin #4	13.963	16.903	15.433	15	0.3191	0.109
Bin #5	16.903	19.843	18.373	6	0.1277	0.043
Bin #6	19.843	22.783	21.313	2	0.0426	0.014
Bin #7	22.783	25.722	24.252	3	0.0638	0.022

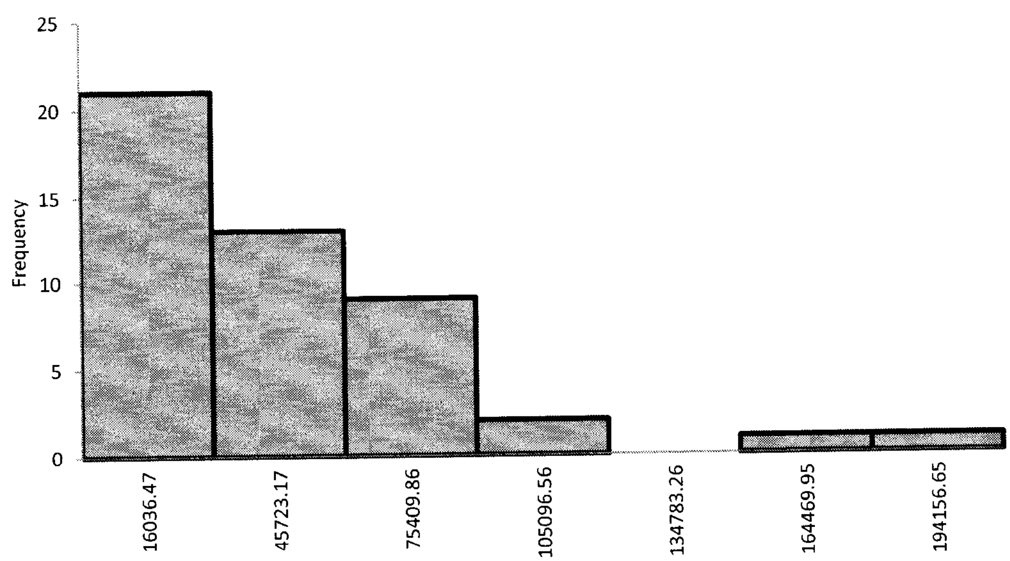
Histogram of Speed / Data Set #2



Total Installed Power / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	1193.12	30879.82	16036.47	21	0.4468	0.0000151
Bin #2	30879.82	60566.51	45723.17	13	0.2766	0.0000093
Bin #3	60566.51	90253.21	75409.86	9	0.1915	0.0000065
Bin #4	90253.21	119939.91	105096.56	2	0.0426	0.0000014
Bin #5	119939.91	149626.61	134783.26	0	0.0000	0.0000000
Bin #6	149626.61	179313.30	164469.95	1	0.0213	0.0000007
Bin #7	179313.30	209000.00	194156.65	1	0.0213	0.0000007

Histogram of Total Installed Power / Data Set #2

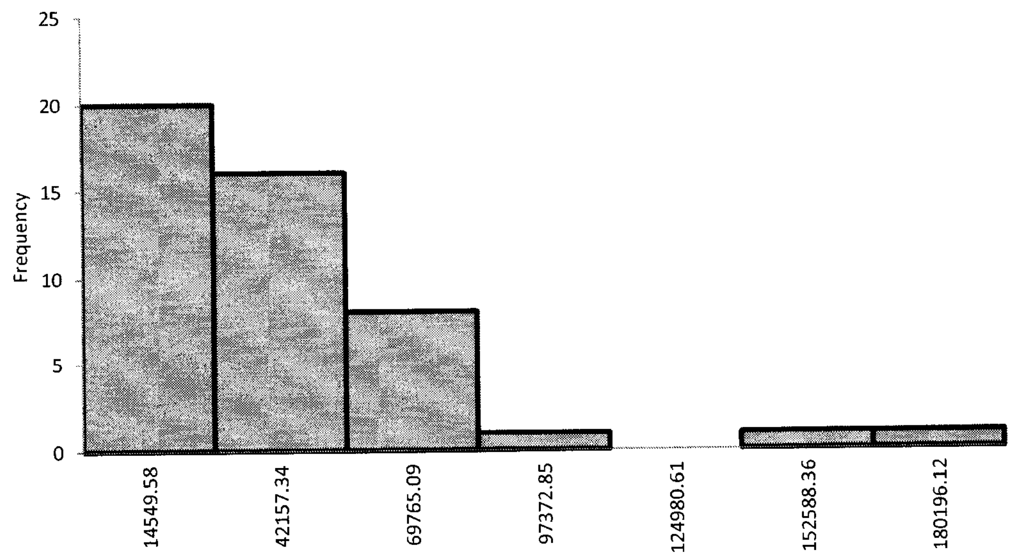


Propulsion Power / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	745.70	28353.46	14549.58	20	0.4255	0.0000154
Bin #2	28353.46	55961.21	42157.34	16	0.3404	0.0000123

Bin #3	55961.21	83568.97	69765.09	8	0.1702	0.0000062
Bin #4	83568.97	111176.73	97372.85	1	0.0213	0.0000008
Bin #5	111176.73	138784.49	124980.61	0	0.0000	0.0000000
Bin #6	138784.49	166392.24	152588.36	1	0.0213	0.0000008
Bin #7	166392.24	194000.00	180196.12	1	0.0213	0.0000008

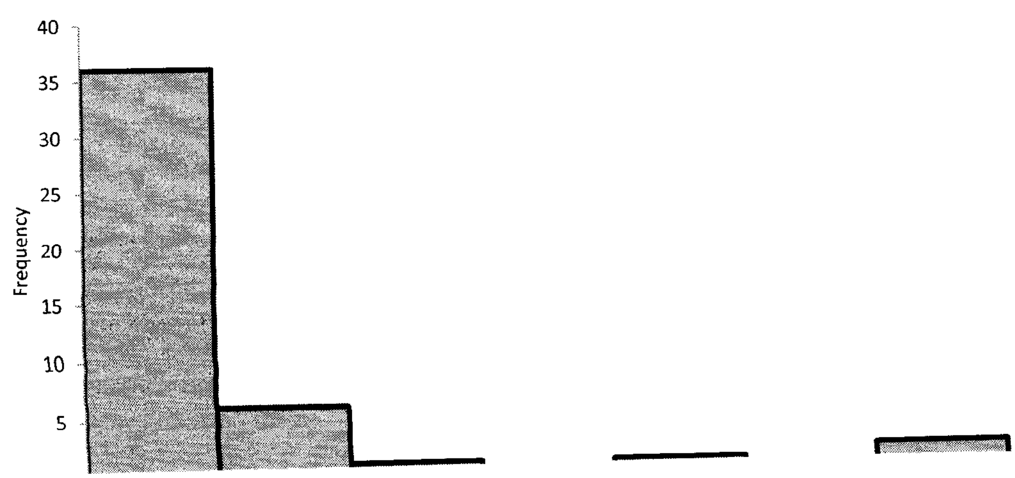
Histogram of Propulsion Power / Data Set #2

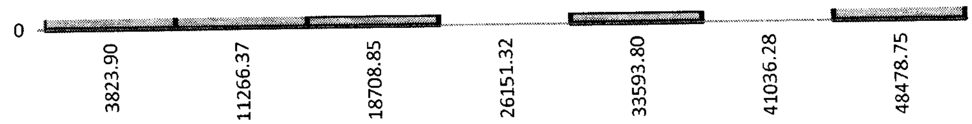


Installed Electrical Power / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	102.66	7545.13	3823.90	36	0.7826	0.000105
Bin #2	7545.13	14987.61	11266.37	6	0.1304	0.000018
Bin #3	14987.61	22430.09	18708.85	1	0.0217	0.000003
Bin #4	22430.09	29872.56	26151.32	0	0.0000	0.000000
Bin #5	29872.56	37315.04	33593.80	1	0.0217	0.000003
Bin #6	37315.04	44757.51	41036.28	0	0.0000	0.000000
Bin #7	44757.51	52199.99	48478.75	2	0.0435	0.000006

Histogram of Installed Electrical Power / Data Set #2

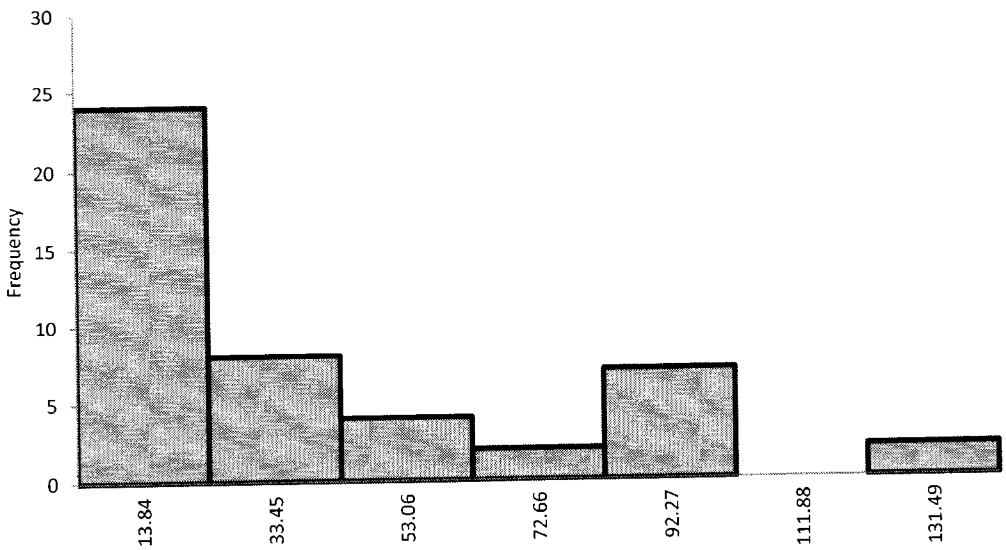




Transport Factor (Prop Power) / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	4.03	23.64	13.84	24	0.5106	0.0260
Bin #2	23.64	43.25	33.45	8	0.1702	0.0087
Bin #3	43.25	62.86	53.06	4	0.0851	0.0043
Bin #4	62.86	82.47	72.66	2	0.0426	0.0022
Bin #5	82.47	102.08	92.27	7	0.1489	0.0076
Bin #6	102.08	121.69	111.88	0	0.0000	0.0000
Bin #7	121.69	141.29	131.49	2	0.0426	0.0022

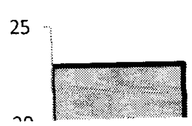
Histogram of Transport Factor (Prop Power) / Data Set #2

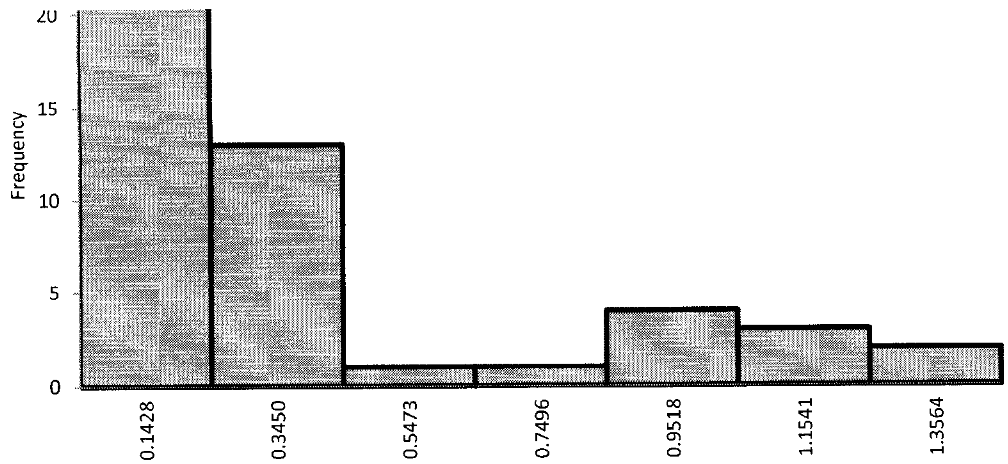


Specific Power / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	0.0416	0.2439	0.1428	23	0.4894	2.42
Bin #2	0.2439	0.4462	0.3450	13	0.2766	1.37
Bin #3	0.4462	0.6484	0.5473	1	0.0213	0.11
Bin #4	0.6484	0.8507	0.7496	1	0.0213	0.11
Bin #5	0.8507	1.0530	0.9518	4	0.0851	0.42
Bin #6	1.0530	1.2552	1.1541	3	0.0638	0.32
Bin #7	1.2552	1.4575	1.3564	2	0.0426	0.21

Histogram of Specific Power / Data Set #2

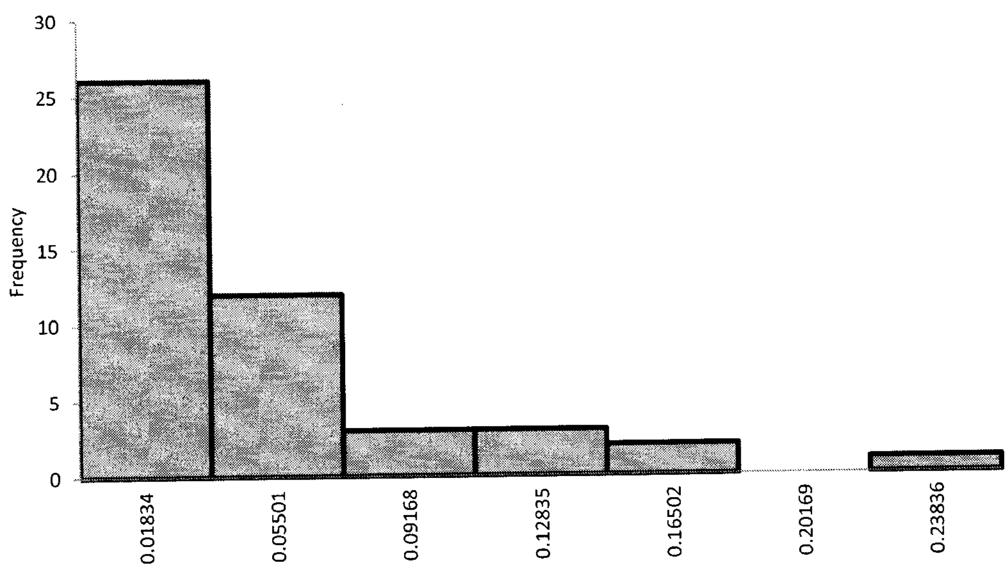




Specific Electrical Power / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	0.00000	0.03667	0.01834	26	0.5532	15.1
Bin #2	0.03667	0.07334	0.05501	12	0.2553	7.0
Bin #3	0.07334	0.11001	0.09168	3	0.0638	1.7
Bin #4	0.11001	0.14668	0.12835	3	0.0638	1.7
Bin #5	0.14668	0.18335	0.16502	2	0.0426	1.2
Bin #6	0.18335	0.22002	0.20169	0	0.0000	0.0
Bin #7	0.22002	0.25669	0.23836	1	0.0213	0.6

Histogram of Specific Electrical Power / Data Set #2

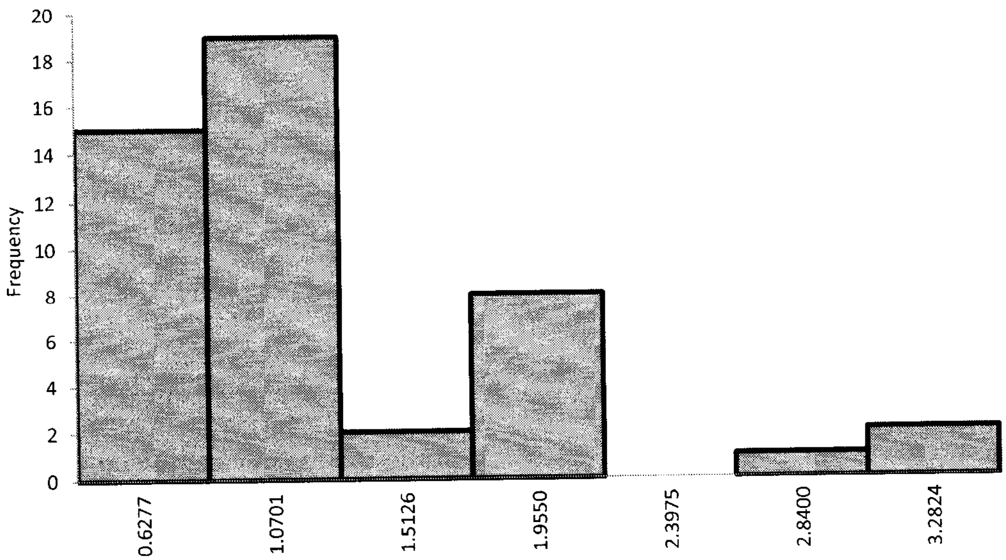


Vol. Fr. # / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	0.4064	0.8489	0.6277	15	0.3191	0.72
Bin #2	0.8489	1.2913	1.0701	19	0.4043	0.91
Bin #3	1.2913	1.7338	1.5126	2	0.0426	0.10

Bin #4	1.7338	2.1763	1.9550	8	0.1702	0.38
Bin #5	2.1763	2.6187	2.3975	0	0.0000	0.00
Bin #6	2.6187	3.0612	2.8400	1	0.0213	0.05
Bin #7	3.0612	3.5036	3.2824	2	0.0426	0.10

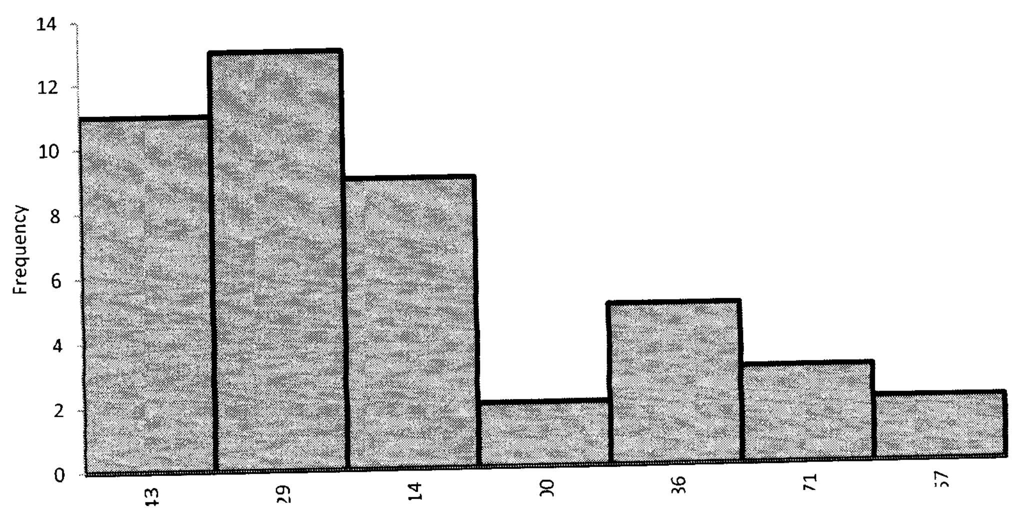
Histogram of Vol. Fr. # / Data Set #2



Range / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	300.00	2542.86	1421.43	11	0.2444	0.000109
Bin #2	2542.86	4785.71	3664.29	13	0.2889	0.000129
Bin #3	4785.71	7028.57	5907.14	9	0.2000	0.000089
Bin #4	7028.57	9271.43	8150.00	2	0.0444	0.000020
Bin #5	9271.43	11514.29	10392.86	5	0.1111	0.000050
Bin #6	11514.29	13757.14	12635.71	3	0.0667	0.000030
Bin #7	13757.14	16000.00	14878.57	2	0.0444	0.000020

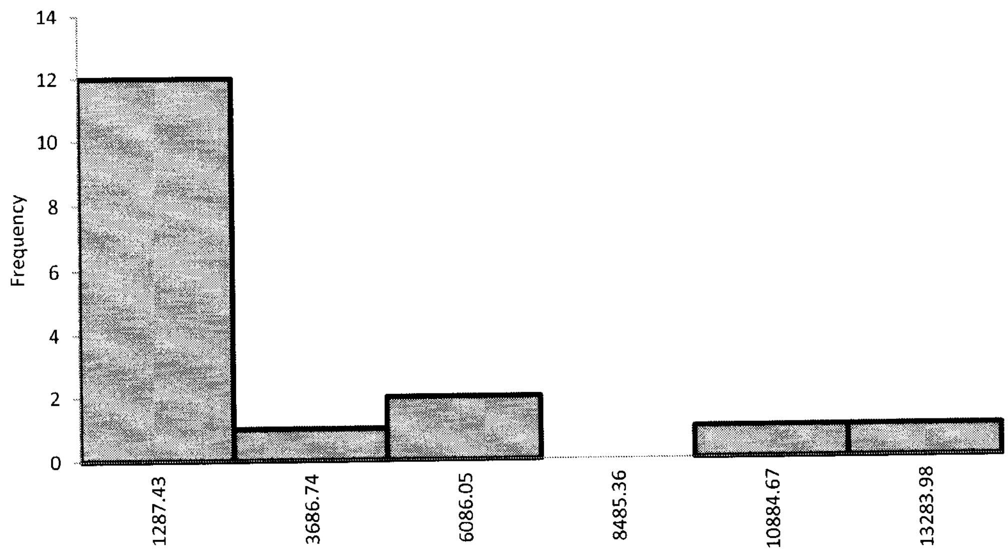
Histogram of Range / Data Set #2



Electrical Load / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	87.77	2487.08	1287.43	12	0.7059	0.000294
Bin #2	2487.08	4886.39	3686.74	1	0.0588	0.000025
Bin #3	4886.39	7285.70	6086.05	2	0.1176	0.000049
Bin #4	7285.70	9685.01	8485.36	0	0.0000	0.000000
Bin #5	9685.01	12084.32	10884.67	1	0.0588	0.000025
Bin #6	12084.32	14483.63	13283.98	1	0.0588	0.000025

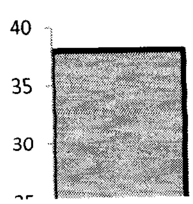
Histogram of Electrical Load / Data Set #2



Crew Size / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	5.00	904.29	454.64	38	0.8085	0.00090
Bin #2	904.29	1803.57	1353.93	2	0.0426	0.00005
Bin #3	1803.57	2702.86	2253.21	2	0.0426	0.00005
Bin #4	2702.86	3602.14	3152.50	4	0.0851	0.00009
Bin #5	3602.14	4501.43	4051.79	0	0.0000	0.00000
Bin #6	4501.43	5400.71	4951.07	0	0.0000	0.00000
Bin #7	5400.71	6300.00	5850.36	1	0.0213	0.00002

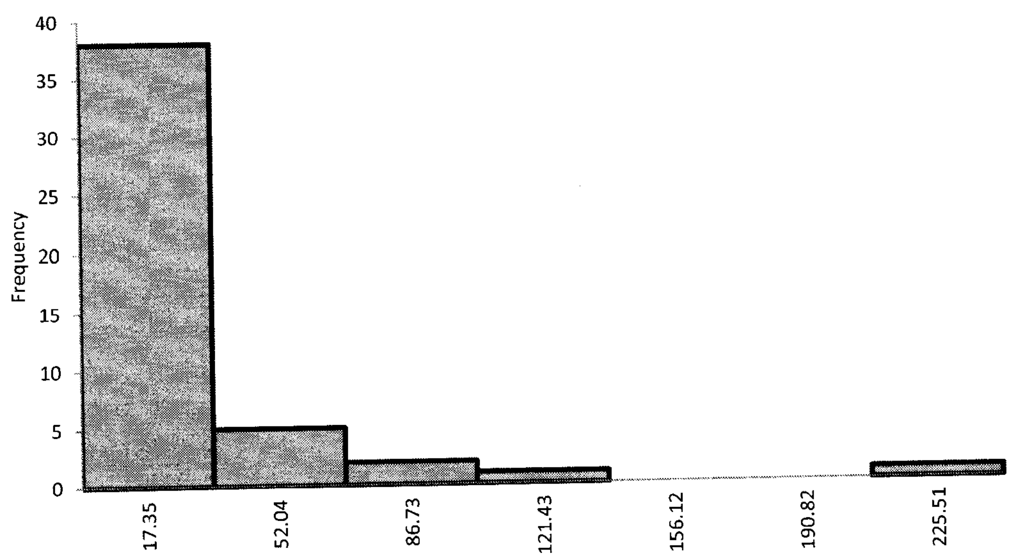
Histogram of Crew Size / Data Set #2



Elec Pwr/Crew Ratio / Data Set #2

Histogram	Bin Min	Bin Max	Bin Midpoint	Freq.	Rel. Freq.	Prb. Density
Bin #1	0.00	34.69	17.35	38	0.8085	0.0233
Bin #2	34.69	69.39	52.04	5	0.1064	0.0031
Bin #3	69.39	104.08	86.73	2	0.0426	0.0012
Bin #4	104.08	138.78	121.43	1	0.0213	0.0006
Bin #5	138.78	173.47	156.12	0	0.0000	0.0000
Bin #6	173.47	208.16	190.82	0	0.0000	0.0000
Bin #7	208.16	242.86	225.51	1	0.0213	0.0006

Histogram of Elec Pwr/Crew Ratio / Data Set #2



StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Tuesday, April 07, 2015
Updating: Static
Variable: Transmission

Multiple Regression for Transmission Summary	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.7028	0.4939	0.4007	0.310498893

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	7	3.575567053	0.510795293	5.2982	0.0003
Unexplained	38	3.663563382	0.096409563		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	8.468574683	5.578258699	1.5181	0.1373	-2.824019671	19.76116904
Class Commissioned Since	-0.003938748	0.002803305	-1.4050	0.1681	-0.009613743	0.001736247
Vessel Weight	-2.41142E-08	1.37124E-08	-1.7586	0.0867	-5.18735E-08	3.64518E-09
Speed	0.016704028	0.012887561	1.2961	0.2027	-0.009385475	0.042793532
Propulsion Power	1.76804E-06	2.60104E-06	0.6797	0.5008	-3.4975E-06	7.03358E-06
Installed Electrical Power	-1.83402E-05	5.20967E-06	-3.5204	0.0011	-2.88866E-05	-7.79373E-06
Transport Factor (Prop Power)	0.000118666	0.002151382	0.0552	0.9563	-0.004236578	0.00447391
Crew Size	0.000399426	0.000168621	2.3688	0.0230	5.80709E-05	0.00074078

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Tuesday, April 07, 2015
Updating: Static
Variable: Installed Electrical Power

Multiple Regression for Installed Electrical Power *Summary*	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.6469	0.4184	0.3290	9543.716627

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	6	2555844016	425974002.6	4.6768	0.0011
Unexplained	39	3552218555	91082527.05		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	-467688.3225	154237.1674	-3.0323	0.0043	-779662.4407	-155714.2044
Class Commissioned Since	237.0597234	77.35210245	3.0647	0.0039	80.60032813	393.5191187
Vessel Weight	0.000116646	0.000421061	0.2770	0.7832	-0.00073503	0.000968321
Speed	60.39263169	396.0032531	0.1525	0.8796	-740.5995527	861.3848161
Propulsion Power	-0.069412951	0.079171137	-0.8767	0.3860	-0.22955169	0.090725789
Transport Factor (Prop Power)	18.87762053	66.05728109	0.2858	0.7766	-114.7358421	152.4910832
Crew Size	4.331102394	5.136234983	0.8432	0.4042	-6.057913469	14.72011826

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Thursday, March 26, 2015
Updating: Static
Variable: Transmission

Multiple Regression for Transmission Summary	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.7182	0.5158	0.4111	0.307790605

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	8	3.733933353	0.466741669	4.9268	0.0003
Unexplained	37	3.505197082	0.094735056		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	8.815000388	5.5360907	1.5923	0.1198	-2.402184864	20.03218564
Class Commissioned Since	-0.004155269	0.002783895	-1.4926	0.1440	-0.009795976	0.001485439
Vessel Weight	-2.23787E-08	1.36589E-08	-1.6384	0.1098	-5.00543E-08	5.29691E-09
Speed	0.022143173	0.013449976	1.6463	0.1082	-0.005109068	0.049395414
Total Installed Power	1.40979E-05	1.09038E-05	1.2929	0.2040	-7.99534E-06	3.61912E-05
Propulsion Power	-1.24283E-05	1.12786E-05	-1.1019	0.2776	-3.52809E-05	1.04243E-05
Installed Electrical Power	-2.90716E-05	9.77552E-06	-2.9739	0.0052	-4.88787E-05	-9.26453E-06
Transport Factor (Prop Power)	0.000651303	0.002172042	0.2999	0.7660	-0.003749671	0.005052277
Crew Size	0.000346061	0.00017217	2.0100	0.0518	-2.78917E-06	0.000694911

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Thursday, March 26, 2015
Updating: Static
Variable: Installed Electrical Power

Multiple Regression for Installed Electrical Power Summary	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.9153	0.8377	0.8078	5107.682134

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	7	5116702733	730957533.3	28.0185	< 0.0001
Unexplained	38	991359837.6	26088416.78		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Upper
Constant	-107251.1416	90207.05667	-1.1889	0.2418	-289865.7807	75363.49743
Class Commissioned Since	51.61365433	45.43273463	1.1360	0.2631	-40.36010851	143.5874172
Vessel Weight	0.000149138	0.000225371	0.6617	0.5121	-0.0003071	0.000605377
Speed	382.2455006	214.4113851	1.7828	0.0826	-51.80765604	816.2986572
Total Installed Power	0.947070441	0.095590192	9.9076	< 0.0001	0.753558214	1.140582668
Propulsion Power	-0.973053191	0.100568365	-9.6755	< 0.0001	-1.176643201	-0.76946318
Transport Factor (Prop Power)	41.04990589	35.42382144	1.1588	0.2538	-30.66187151	112.7616833
Crew Size	-2.376192325	2.830987393	-0.8394	0.4065	-8.107226682	3.354842031

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Normalized to Most E Power (52 Mw)

Multiple Regression for Normalized to Most E Power (52 Mw) Summary	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.6433	0.4139	0.3567	0.17901073

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	4	0.927784741	0.231946185	7.2382	0.0002
Unexplained	41	1.313838502	0.032044842		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Upper**
Constant	-1.0009E-16	0.026393692	0.0000	1.0000	-0.053303143	0.053303143
Normalized to Largest Crew (6300)	0.739070383	0.213977861	3.4540	0.0013	0.306933325	1.171207441
Normalized to Most Power (194 MW)	-0.214023421	0.215779569	-0.9919	0.3271	-0.6497991	0.221752259
Normalized to Fastest (25.7 m/s)	-0.019376138	0.168933174	-0.1147	0.9092	-0.360543604	0.321791327
Normalized to Oldest (79)	-0.356790607	0.112840973	-3.1619	0.0029	-0.584677574	-0.12890364

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Normalized to Most E Power (52 Mw)

Multiple Regression for Normalized to Most E Power (52 Mw) Summary	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.5205	0.2710	0.2189	0.197255461

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	3	0.607415131	0.20247171	5.2036	0.0038
Unexplained	42	1.634208111	0.038909717		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Upper**
Constant	-7.62319E-17	0.029083731	0.0000	1.0000	-0.058693345	0.058693345
Normalized to Largest Crew (6300)	0.751618956	0.235745875	3.1883	0.0027	0.275864519	1.227373394
Normalized to Most Power (194 MW)	-0.231319996	0.237695351	-0.9732	0.3360	-0.711008634	0.248368643
Normalized to Fastest (25.7 m/s)	-0.022763678	0.186147059	-0.1223	0.9033	-0.398423652	0.352896295

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Normalized to Most E Power (52 Mw)

Multiple Regression for Normalized to Most E Power (52 Mw) Summary	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.9755	0.9516	0.9032	0.129537014

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	4	1.320038124	0.330009531	19.6670	0.0068
Unexplained	4	0.067119352	0.016779838		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	0.154435801	0.098965655	1.5605	0.1937	-0.120336907	0.42920851
Normalized to Largest Crew (6300)	2.367684707	0.352885037	6.7095	0.0026	1.387918773	3.347450641
Normalized to Most Power (194 MW)	-1.762718011	0.820094085	-2.1494	0.0980	-4.039664219	0.514228198
Normalized to Fastest (25.7 m/s)	1.507573072	0.439084676	3.4334	0.0265	0.288478572	2.726667572
Normalized to Oldest (79)	-0.794417651	0.450595513	-1.7630	0.1527	-2.045471357	0.456636055

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Normalized to Most E Power (52 Mw)

Multiple Regression for Normalized to Most E Power (52 Mw) *Summary*	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.9560	0.9140	0.8624	0.154451452

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	3	1.267881219	0.422627073	17.7163	0.0043
Unexplained	5	0.119276256	0.023855251		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	0.301556388	0.06343821	4.7535	0.0051	0.138483279	0.464629498
Normalized to Largest Crew (6300)	2.334325199	0.420151721	5.5559	0.0026	1.254290817	3.414359582
Normalized to Most Power (194 MW)	-0.882110154	0.775541194	-1.1374	0.3069	-2.87570226	1.111481952
Normalized to Fastest (25.7 m/s)	1.160042366	0.467813134	2.4797	0.0559	-0.042509579	2.362594311

StatTools Report

Analysis:	Regression
Performed By:	Brian Waller
Date:	Sunday, March 22, 2015
Updating:	Static
Variable:	Normalized to Most E Power (52 Mw)

Multiple Regression for Normalized to Most E Power (52 Mw) Summary	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.6443	0.4151	0.3420	0.064262584

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	4	0.093773897	0.023443474	5.6768	0.0014
Unexplained	32	0.132149749	0.00412968		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Upper**
Constant	-0.052537431	0.010996497	-4.7777	< 0.0001	-0.074936562	-0.030138299
Normalized to Largest Crew (6300)	0.171886282	0.089399901	1.9227	0.0635	-0.010215356	0.353987921
Normalized to Most Power (194 MW)	0.093312644	0.082991322	1.1244	0.2692	-0.075735146	0.262360435
Normalized to Fastest (25.7 m/s)	-0.04196013	0.068546449	-0.6121	0.5448	-0.181584677	0.097664417
Normalized to Oldest (79)	-0.087220907	0.047187711	-1.8484	0.0738	-0.183339129	0.008897315

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Installed Electrical Power

Multiple Regression for Installed Electrical Power Summary	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.6433	0.4139	0.3567	9344.358503

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	4	2528064102	632016025.4	7.2382	0.0002
Unexplained	41	3579998469	87317035.83		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	11903.6121	5045.243284	2.3594	0.0231	1714.536585	22092.68762
Vessel Age	-235.7527403	74.56073105	-3.1619	0.0029	-386.3311914	-85.17428914
Speed	-39.32141803	342.8284751	-0.1147	0.9092	-731.6775694	653.0347333
Propulsion Power	-0.057587735	0.058060266	-0.9919	0.3271	-0.17484282	0.05966735
Crew Size	6.123724972	1.772959118	3.4540	0.0013	2.543161395	9.704288549

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Installed Electrical Power

Multiple Regression for Installed Electrical Power Summary	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.5205	0.2710	0.2189	10296.73329

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	3	1655108476	551702825.2	5.2036	0.0038
Unexplained	42	4452954095	106022716.5		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Upper**
Constant	5021.950115	5015.561555	1.0013	0.3224	-5099.862889	15143.76312
Speed	-46.19600147	377.7618745	-0.1223	0.9033	-808.5503285	716.1583256
Propulsion Power	-0.062241761	0.063957192	-0.9732	0.3360	-0.1913126	0.066829077
Crew Size	6.227698849	1.953322631	3.1883	0.0027	2.285734189	10.16966351

StatTools Report

Analysis:	Regression
Performed By:	Brian Waller
Date:	Sunday, March 22, 2015
Updating:	Static
Variable:	Installed Electrical Power

Multiple Regression for Installed Electrical Power ***Summary***	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.9755	0.9516	0.9032	6761.830941

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	4	3596891440	899222860.1	19.6670	0.0068
Unexplained	4	182889430.7	45722357.67		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95%** Lower	Upper
Constant	-7540.780915	8269.340031	-0.9119	0.4134	-30500.14957	15418.58774
Vessel Age	-524.9189143	297.7352116	-1.7630	0.1527	-1351.564385	301.7265567
Speed	3059.428567	891.0667263	3.4334	0.0265	585.4307168	5533.426418
Propulsion Power	-0.47429827	0.220664453	-2.1494	0.0980	-1.08696101	0.138364471
Crew Size	19.61795562	2.923904089	6.7095	0.0026	11.49989642	27.73601481

StatTools Report

Analysis:	Regression
Performed By:	Brian Waller
Date:	Sunday, March 22, 2015
Updating:	Static
Variable:	Installed Electrical Power

Multiple Regression for Installed Electrical Power ***Summary***	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.9560	0.9140	0.8624	8062.364422

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	3	3454772271	1151590757	17.7163	0.0043
Unexplained	5	325008600.4	65001720.07		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Confidence Interval 95% Upper**
Constant	-14512.08917	8659.562481	-1.6758	0.1546	-36772.20319	7748.024847
Speed	2354.159025	949.3674921	2.4797	0.0559	-86.26780512	4794.585856
Propulsion Power	-0.237351248	0.208676512	-1.1374	0.3069	-0.773771299	0.299068804
Crew Size	19.34154832	3.481256518	5.5559	0.0026	10.39269355	28.29040309

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Installed Electrical Power

Multiple Regression for Installed Electrical Power Summary	Multiple R	R-Square	Adjusted R-Square	StErr of Estimate
	0.6443	0.4151	0.3420	3354.506284

ANOVA Table	Degrees of Freedom	Sum of Squares	Mean of Squares	F-Ratio	p-Value
Explained	4	255518776.2	63879694.06	5.6768	0.0014
Unexplained	32	360086797.1	11252712.41		

Regression Table	Coefficient	Standard Error	t-Value	p-Value	Confidence Interval 95% Lower	Confidence Interval 95% Upper
Constant	4285.775944	2333.723812	1.8365	0.0756	-467.863904	9039.415792
Vessel Age	-57.63203243	31.17972264	-1.8484	0.0738	-121.1430491	5.878984249
Speed	-85.15276826	139.1063346	-0.6121	0.5448	-368.5030994	198.1975629
Propulsion Power	0.025107831	0.022330651	1.1244	0.2692	-0.020378216	0.070593878
Crew Size	1.424200378	0.740741906	1.9227	0.0635	-0.08464151	2.933042266

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Normalized to Most E Power (52 Mw)

Multiple Regression for Normalized to Most E Power (52 Mw) ***Summary***	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.5938	0.3526	0.2938	0.066573919

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	3	0.079664783	0.026554928	5.9915	0.0022
Unexplained	33	0.146258863	0.004432087		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Confidence Interval 95% Upper**
Constant	-0.057166361	0.011092656	-5.1535	< 0.0001	-0.079734539	-0.034598183
Normalized to Largest Crew (6300)	0.161499382	0.092432206	1.7472	0.0899	-0.026555355	0.349554119
Normalized to Most Power (194 MW)	0.092150873	0.08597381	1.0718	0.2916	-0.082764158	0.267065904
Normalized to Fastest (25.7 m/s)	-0.024668487	0.070347421	-0.3507	0.7281	-0.167791392	0.118454418

StatTools Report

Analysis: Regression
Performed By: Brian Waller
Date: Sunday, March 22, 2015
Updating: Static
Variable: Installed Electrical Power

Multiple Regression for Installed Electrical Power Summary	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.5938	0.3526	0.2938	3475.157994

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	3	217073711.6	72357903.86	5.9915	0.0022
Unexplained	33	398531861.8	12076723.08		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95% Lower**	**Confidence Interval 95% Upper**
Constant	1885.59434	2008.836915	0.9386	0.3547	-2201.415094	5972.603774
Speed	-50.06156967	142.76118	-0.3507	0.7281	-340.5113743	240.3882349
Propulsion Power	0.024795231	0.023133155	1.0718	0.2916	-0.022269527	0.071859988
Crew Size	1.338137508	0.765866717	1.7472	0.0899	-0.220030043	2.89630506

StatTools Report

Analysis:	Regression
Performed By:	Brian Waller
Date:	Sunday, March 22, 2015
Updating:	Static
Variable:	Installed Electrical Power

Multiple Regression for Installed Electrical Power ***Summary***	**Multiple R**	**R-Square**	**Adjusted R-Square**	**StErr of Estimate**
	0.5938	0.3526	0.2938	3475.157994

ANOVA Table	**Degrees of Freedom**	**Sum of Squares**	**Mean of Squares**	**F-Ratio**	**p-Value**
Explained	3	217073711.6	72357903.86	5.9915	0.0022
Unexplained	33	398531861.8	12076723.08		

Regression Table	**Coefficient**	**Standard Error**	**t-Value**	**p-Value**	**Confidence Interval 95%** Lower	Upper
Constant	1885.59434	2008.836915	0.9386	0.3547	-2201.415094	5972.603774
Speed	-50.06156967	142.76118	-0.3507	0.7281	-340.5113743	240.3882349
Propulsion Power	0.024795231	0.023133155	1.0718	0.2916	-0.022269527	0.071859988
Crew Size	1.338137508	0.765866717	1.7472	0.0899	-0.220030043	2.89630506

Appendix C – Matlab Scripts & Results

Matlab Scripts

Matlab Script for Principal Component Analysis (electrical dataset example):

```
clear all
filename='ProcessedDataE'
E=xlsread(filename)
[coeff,score,latent,tsquared,explained,mu]=pca(E)
```

Matlab Script for Neural Network construction and training (electrical dataset example):

```
% Solve an Input-Output Fitting problem with a Neural Network
% Script generated by NFTOOL
% Created Tue Mar 24 15:47:45 CDT 2015
% This script assumes these variables are defined:
%   data - input data.
%   Epwr - target data.
inputs = data;
targets = Epwr;
% Create a Fitting Network
hiddenLayerSize = 10;
net = fitnet(hiddenLayerSize);
% Setup Division of Data for Training, Validation, Testing
net.divideParam.trainRatio = 70/100;
net.divideParam.valRatio = 15/100;
net.divideParam.testRatio = 15/100;
% Train the Network
[net,tr] = train(net,inputs,targets);
% Test the Network
outputs = net(inputs);
errors = gsubtract(targets,outputs);
performance = perform(net,targets,outputs)
% View the Network
view(net)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotperform(tr)
%figure, plottrainstate(tr)
%figure, plotfit(net,inputs,targets)
%figure, plotregression(targets,outputs)
%figure, ploterrhist(errors)
```

Neural Network Results

Neural Network 1

Weight Matrix for Layer 1

$$\begin{bmatrix} -0.199 & 1.543 & 1.497 \\ 46.800 & 77.886 & -210.97 \\ -239.880 & -5.539 & -69.046 \\ 348.358 & -589.073 & 137.198 \\ -52.358 & 88.278 & 113.731 \\ -0.744 & 1.456 & 1.313 \\ -25.462 & 8.170 & 6.377 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} -3.324 \\ -44.269 \\ 76.346 \\ -32.677 \\ -46.332 \\ -2.763 \\ -2.878 \end{bmatrix}$$

Weight Matrix for Layer 2

$$\begin{bmatrix} -111.804 & 0.253 & 1.211 & 0.383 & -1.991 & 229.301 & -1.508 \end{bmatrix}$$

Bias Matrix for Layer 2

$$\begin{bmatrix} 112.746 \end{bmatrix}$$

Neural Network 2

Weight Matrix for Layer 1

$$\begin{bmatrix} -0.199 & 1.543 & 1.497 \\ 46.800 & 77.886 & -210.97 \\ -239.880 & -5.539 & -69.046 \\ 348.358 & -589.073 & 137.198 \\ -52.358 & 88.278 & 113.731 \\ -0.744 & 1.456 & 1.313 \\ -25.462 & 8.170 & 6.377 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} -3.324 \\ -44.269 \\ 76.346 \\ -32.677 \\ -46.332 \\ -2.763 \\ -2.878 \end{bmatrix}$$

Weight Matrix for Layer 2

$$\begin{bmatrix} -111.804 & 0.253 & 1.211 & 0.383 & -1.991 & 229.301 & -1.508 \end{bmatrix}$$

Bias Matrix for Layer 2

$$\begin{bmatrix} 112.746 \end{bmatrix}$$

Neural Network 3

Weight Matrix for Layer 1

$$\begin{bmatrix} 18.640 & 7.744 & 3.714 \\ -134.534 & 452.873 & 58.787 \\ -17.774 & -2.415 & -3.682 \\ -6.770 & 5.138 & -10.228 \\ 6.973 & -5.283 & 10.466 \\ -55.740 & 43.856 & 71.567 \\ 1.036 & 1.024 & -8.069 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} -5.318 \\ 76.808 \\ 4.686 \\ 1.501 \\ -1.493 \\ -28.843 \\ 2.484 \end{bmatrix}$$

Weight Matrix for Layer 2

$$\begin{bmatrix} -271.822 & 0.049 & -274.671 & 51.214 & 48.23 & -2.108 & -5.278 \end{bmatrix}$$

Bias Matrix for Layer 2

$$\begin{bmatrix} 2.990 \end{bmatrix}$$

Neural Network 4

Weight Matrix for Layer 1

$$\begin{bmatrix} 0.913 & 0.888 & -0.217 & 0.112 & -2.052 & 0.111 \\ 1.231 & 1.236 & 1.068 & 0.246 & 1.116 & -1.965 \\ -17.256 & 18.708 & 0.481 & 16.658 & 0.905 & 7.820 \\ 3.817 & -1.732 & 0.918 & -4.594 & 1.309 & -1.262 \\ -6.779 & -15.941 & -2.570 & -17.800 & 3.396 & -27.857 \\ -0.937 & -3.895 & 4.501 & 9.522 & -2.520 & 2.026 \\ 2.384 & 5.494 & -1.690 & 3.428 & -10.071 & 0.305 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} -0.926 \\ -4.590 \\ 1.053 \\ -2.368 \\ -3.962 \\ 3.412 \\ 1.742 \end{bmatrix}$$

Weight Matrix for Layer 2

$$\begin{bmatrix} -0.814 & -1.376 & -2.929 & 8.666 & -2.827 & 2.357 & 5.414 \end{bmatrix}$$

Bias Matrix for Layer 2

$$\begin{bmatrix} 0.086 \end{bmatrix}$$

Neural Network 5

Weight Matrix for Layer 1

$$\begin{bmatrix} -21.171 & -18.731 & -20.870 & 46.854 \\ 14.155 & -20.024 & 16.890 & -14.980 \\ 12.016 & -4.857 & 12.368 & -17.902 \\ -16.299 & 30.240 & -19.904 & 20.520 \\ 195.147 & -41.305 & 44.746 & 23.099 \\ 78.795 & 2.412 & 33.546 & 34.586 \\ 60.780 & -85.636 & 23.323 & -44.223 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} -8.696 \\ 3.287 \\ 3.197 \\ -4.205 \\ 17.726 \\ 14.891 \\ 20.479 \end{bmatrix}$$

Weight Matrix for Layer 2

$$[43.641 \quad -218.459 \quad 61.812 \quad -117.115 \quad 98.488 \quad -99.677 \quad 83.671]$$

Bias Matrix for Layer 2

$$[1.687]$$

Neural Network 6

Weight Matrix for Layer 1

$$\begin{bmatrix} 5.138 & -4.667 & 9.171 & 11.444 \\ 19.519 & -0.704 & -2.696 & -1.807 \\ 8.903 & 0.183 & 1.517 & -11.258 \\ -22.734 & 19.517 & -23.929 & 20.150 \\ -13.843 & 14.366 & -16.218 & 14.562 \\ 19.155 & -1.667 & 3.163 & -11.953 \\ -2.721 & 3.820 & -6.257 & -10.762 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} 3.498 \\ -0.240 \\ -1.030 \\ 6.475 \\ 4.824 \\ -0.235 \\ -2.735 \end{bmatrix}$$

Weight Matrix for Layer 2

$$[5.206 \quad -0.1868 \quad -9.991 \quad -11.082 \quad 12.842 \quad 7.586 \quad 7.703]$$

Bias Matrix for Layer 2

$$[-1.942]$$

Neural Network 7

Weight Matrix for Layer 1

$$\begin{bmatrix} 0.049 & -1.997 & 0.963 & 1.315 \\ -0.124 & -1.788 & -2.037 & 1.018 \\ -1.618 & -1.469 & -1.291 & -1.165 \\ 1.763 & 1.405 & 0.554 & 1.421 \\ -0.625 & -2.365 & 1.326 & 0.231 \\ -1.432 & -1.693 & -1.548 & -0.540 \\ 0.930 & -1.284 & 1.588 & 1.678 \\ -0.497 & 0.947 & 1.552 & 1.957 \\ -2.099 & 1.759 & -0.120 & 0.415 \\ -1.324 & 1.679 & -0.788 & 1.586 \\ -2.658 & -0.342 & -0.353 & 0.476 \\ -1.951 & 0.268 & -1.123 & -1.866 \\ 2.328 & -1.059 & 0.042 & -1.042 \\ 2.347 & 1.265 & 0.052 & -0.133 \\ 0.393 & -1.634 & 1.664 & -1.411 \end{bmatrix}$$

Bias Matrix for Layer 1

$$\begin{bmatrix} 2.954 \\ 2.204 \\ 1.930 \\ -1.609 \\ 1.096 \\ 0.777 \\ -0.401 \\ 0.117 \\ -0.394 \\ -0.767 \\ -1.090 \\ -1.340 \\ 1.956 \\ 2.408 \\ 2.756 \end{bmatrix}$$

Weight Matrix for Layer 2

$$[0.415 \quad -0.567 \quad -0.408 \quad -0.274 \quad -0.663 \quad -0.383 \quad -0.893 \quad -0.622 \quad -0.795 \quad -0.758 \quad 0.36 \quad 0.564 \quad 0.760 \quad 0.077]$$

Bias Matrix for Layer 2

$$[0.361]$$

VITA

The author was born in Houston, Texas. He obtained his Bachelor's degree in Naval Architecture and Marine Engineering from the United States Coast Guard Academy in 2008, when he was also commissioned as an officer in the United States Coast Guard. He was billeted onboard the USCGC Confidence, a 210' medium endurance cutter, home ported in Port Canaveral, Fl as a Student Engineer and Damage Control Assistant. He was next assigned in 2010 as a Port Engineer for the 87' Coastal Patrol Boats in New Orleans, LA. In 2013 he joined the University of New Orleans engineering graduate program to pursue dual Masters Degrees in Naval Architecture and Marine Engineering and Engineering Management. Upon his graduation from the University of New Orleans, LT Waller will be reassigned to a Coast Guard cutter home ported in Kodiak, AK.