Installation Services Requirements Determination Analysis: Electrical Services

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Abstract

The U.S. Army is responsible for adequately planning and budgeting for future use of public funds. Part of this planning includes estimating the future cost, or requirement, for the various services that support Army installations around the world. These services range from basic utilities to substance abuse programs, and directly support the Army mission. The Base Operations Support Requirement Model (BRM) provides estimated requirements for 61 services that support Army installations. These estimated requirements comprise more than 70% of total Base Operations Support (BOS) requirements. Currently, Standard Service Costing (SSC) uses historical execution data, installation data, linear regression statistical processes, and quality/funding association rules to forecast future "should-cost" requirements at four distinct levels of service ("Green", "Amber", "Red", and "Black" service levels). This study analyzes the historical performance of these statistical processes and explores alternative methods for determining future service requirements at installation granularity.

Keywords

costing, requirement generation, engineering economics, data analysis

1 Introduction

The Army as well as the other services in the Department of Defense (DoD) are responsible for planning, programming, budgeting, and finally allocating and managing resources approved by Congress. Together these functions make up the Army Planning, Programming, Budgeting and Execution System (PPBES). Planning determines the size, equipment, personnel, and training required for our Army to support the national military strategy. Programming allocates available manpower, dollars, and material among competing requirements, and budgeting converts these decisions to requests for congressional authorizations and appropriations. Execution is the application of resources to achieve program objectives (Department of the Army Economic Analysis Manual, 2001).

During the programming and budgeting process, various proponents in the Army assist in producing the Program Objective Memorandum (POM), a document that outlines proposed Army programs to the Office of the Secretary of Defense (OSD). The POM generally presents proposed program requirements for a 5-year period (Planning, Programming, Budgeting and Execution System: Army Regulation 1-1). As part of this process, the Army Chief of Staff for Installation Management (ACSIM) determines the future installation requirements for 61 of the services that are offered across our installations (such as *Laundry & Dry Cleaning*, *Automation*, and *Electrical* Services). These calculations are conducted 12-28 months prior to the respective POM. For example, during the winter of 2012-2013 ACSIM will finish requirement determination for the POM covering fiscal years 2015 through 2019. For *electrical* services, this process requires analysts in early 2013 to estimate the total cost of electricity for the Army (Active, Reserve, and National Guard components) for each year from 2015 through 2019.

1.1 Background of Base Operations Support Requirements Model (BRM)

The Army Installation Management Headquarters Information (AIM-HI) model was used to generate installation service requirements from 2002 through 2006. The AIM-HI model was renamed to Base Operations Support Requirements Model (BRM) in 2006 at the same time that Installation Management Command (IMCOM) was established (Shelton, 2006).

The BRM process determines the best independently verifiable standard cost of services. Figure 1 outlines the overall BRM process. The process involves integrating various data sources (through the Installations Status Report), conducts statistical analysis in order to relate important service related factors to the services cost (through Standard Service Costing), and then uses the regression output to estimate future costs. These results assist analysts and decision makers build the POM. Later, the actual execution of the program will in turn create data for another iteration of the BRM process.

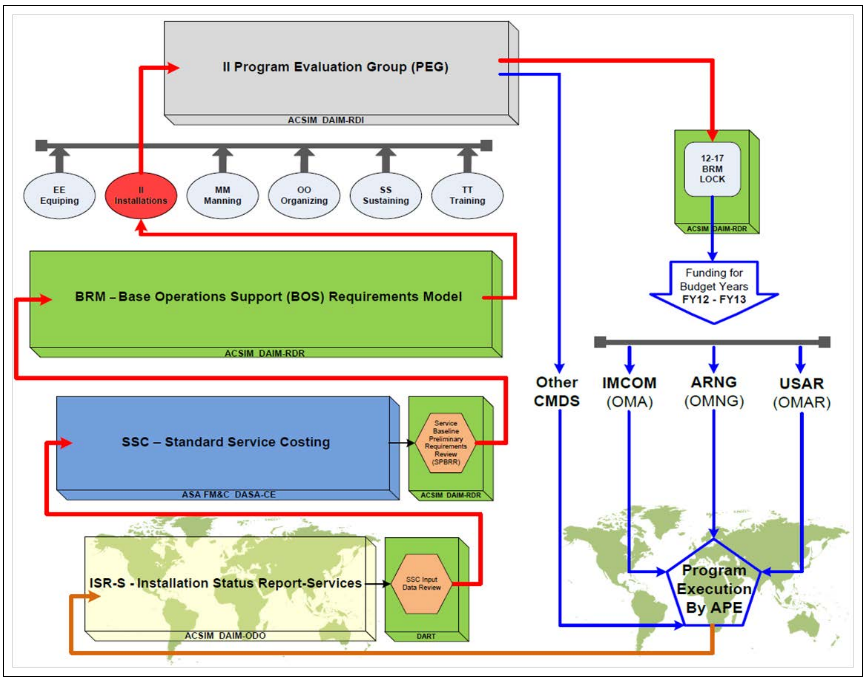


Figure 1: Base Operations Support Requirements Model (BRM) Process Flow

For various reasons, this BRM output has seen reduced usage among the 61 services. Service managers (also called Managment Decision Package managers, or MDEP managers) are currently allowed to create their own estimate with alternative models or methods that they develop, if they determine that the SSC results for their respective service are unsuitable. An increasing number of service level managers are turning to various alternative methodologies in order to generate their service level requirements. As of POM 14-18, only 21 services used the BRM output to generate their requirements. ACSIM saw this trend moving away from BRM increasing as it became apparent that nuances of the new General Fund Enterprise Business System (GFEBS) would make it increasingly difficult to accurately capture historical execution at the service level of granularity, negatively impacting the quality of service level statistical analysis.

1.2 Problem Definition

With these complications in view, ACSIM commissioned our team in 2012 to assist in exploring and validating service level requirement generation. Our task is to document, evaluate and where necessary recommend revised or new procedures for determining accurate requirements for Army Installation Services. This includes process mapping and documenting the current system and process methodology(ies), developing alternatives, performing comparative analyses between the current parametrically modeled requirements and other models created by us or by service managers.

To date we've analyzed *Laundry and Dry Cleaning*, *Leasing*, *Temporary Housing*, *Electrical*, *Heating & Cooling*, *Physical Security*, *Law Enforcement*, and *Custodial* Services. This article will outline our methods, results, and conclusions for *Electrical* Services.

2 Understanding the *Electrical* Service and Related Literature

Electrical services provides the electrical utility throughout Army installations, and is primarily the cost of producing or purchasing electricity. This service does not include installation or maintenance of the distribution system (ISR Data Collection Definition, 2011).

Electrical costs are primarily attributed to the Mega-watt hours (MWh) consumed by the Army. As seen in Figure 2, 98% of the cost is associated with purchasing and/or producing MWh of electricity, purchased both through contract as well as direct payment. Only 2% of the cost is associated with equipment, supplies, civilian pay, and training (ISR Data, 2011). The small amount of civilian pay compensation seen in this service is primarily attributed to those jobs associated with co-generation plants. Our efforts focused on modeling costs associated with the consumption of MWh.

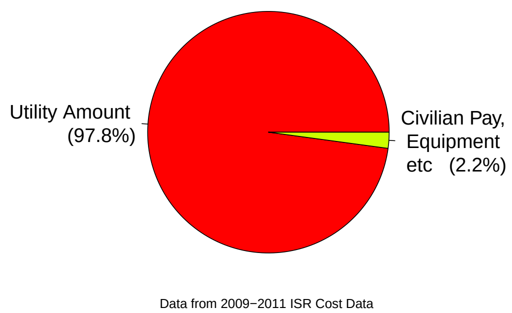
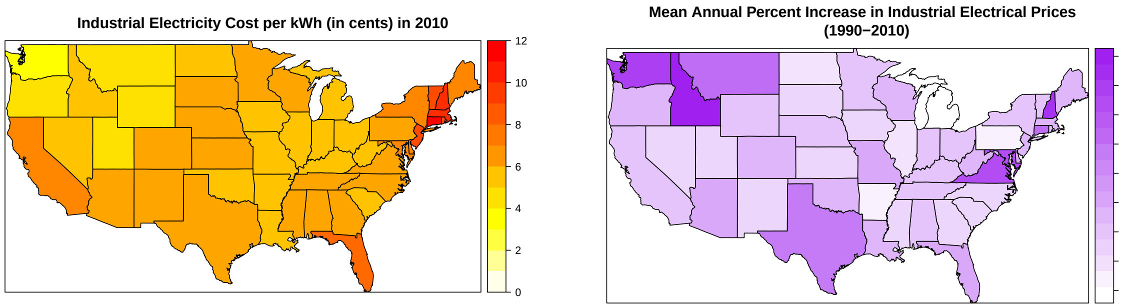


Figure 2: Cost Categories for *Electrical* Expenditure



(a) Spatial variance in Industrial *Electrical* Costs (b) Mean Annual % Increase of Electrical Prices

Figure 3: Geopatial visualization of U.S. electrical costs (EIA Data, 2011)

2.1 Geospatial Analysis

Energy prices vary drastically spatially and temporally across Army installations. As an example, in 2012 the Industrial price per KWh varied from roughly \$0.02 in the Northwest to \$0.12 in the Northeast (U.S. Energy Information Administration Data, 2011). Figure 3a depicts this price variance for the continental United States in 2010. Additionally, Figure 3b demonstrates that the rate of change varies by region. Note that the increase in prices is much higher in the Northwest and the Mid-Atlantic. Of note in Figure 3b is that Pennsylvania has almost no change in price due to historical regulation. Since 2010, Pennsylvania has deregulated their energy pricing, which has caused significant fluctuation in electrical prices there.

We also investigated electric futures markets to compare future market expectations with historic price fluctuations. We primarily looked at the Pennsylvania-New Jersey-Maryland (PJM) Interconnection, which is currently the world's largest competitive wholesale electric market. It currently serves all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, new Jersey, Ohio, North Carolina, Tennessee, Pennsylvania, West Virginia, Virginia, and the District of Columbia. PJM futures are traded at monthly increments for a five year time horizon. Figure 4 shows the national industrial electric price per kilowatt hour (from EIA Data) compared to the market price per kilowatt hour for the 5 year time horizon of PJM. Note that historically the mean annual increase in electric prices is 3.2% over the last 20 years. The markets indicate a mean increase of 3.7% increase in the out years, which is not drastically different than historical realizations. Note that past and future energy price growth does exceed allowable DoD inflation rates, but not by a large margin.

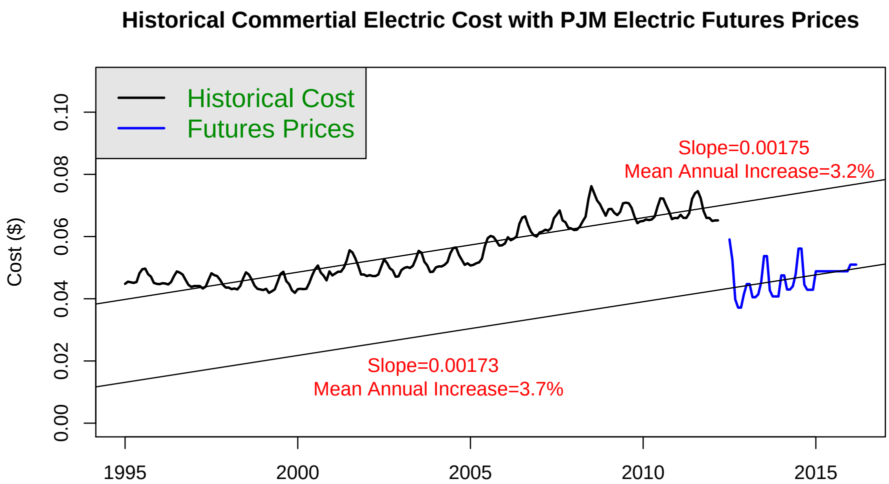


Figure 4: Comparing Historic Industrial Electric Prices (from EIA Data) to PJM Future Prices

2.2 Literature Review

The Department of the Army Economic Analysis Manual (2001) lists four generic classifications of methods used for estimating costs. The *Engineering Approach* is generally an additive methodology in which the costs of distinct processes/components of a service are estimated separately and added together. The *Parametric Approach* is the primary methodology used by Standard Service Costing and involves identifying the parametric statistical relationship between one or more explanatory variables and the cost of a service . The Army Economic Analysis Manual also mentions the *Analogy Approach* and the *Expert Opinion Approach*, but these methodologies were not explored in this study.

The vast majority of literature on electricity forecasting deals with price and demand point estimates over a relatively short time horizon (hours to days). Load forecasting in generally classified by time horizon, with up to 1 day for short-term forecasting, 1 day to 1 year for medium-term load forecasting, and 1-10 years for long-term forecasting [Strinivasan and Lee, 1995]. Alfares and Nazeeruddin (2002) arranged the following nine categories of load forecasting techniques:

- multiple regression
- exponential smoothing
- iterative reweighted least-squares
- adaptive load forecasting
- stochastic time series
- ARMAX models based on genetic algorithms
- fuzzy logic
- neural networks
- knowledge-based expert systems

2.2.1 Industry Perspective

In order to narrow down models for our candidate solutions we interviewed the University of Oregon and Tesla Forecasting Inc. We chose to interview the University of Oregon since a large university campus is similar in many ways to a military base, and we interviewed Tesla Forecasting as one of the industry leaders in electrical load forecasting.

The University of Oregon utilizes a very detailed monitoring program in conjunction with long term price negotiations to accurately predict per square foot usage and cost for every type of building in their inventory. While the Army is moving toward a better monitoring program that may facilitate this approach, currently the detailed monitoring data by type of building is not available. Additionally, price structures and negotiations vary across Army installations.

Tesla Forecasting is one of the three largest electrical forecasting companies in the United States, and provides short and long-term forecasting models to large utility companies in the United State and Britain. Tesla Forecasting utilizes large multi-variate regression models for both short and long term forecasting. Roughly 60% of their variables are weather variables based on detailed weather data collected from weather stations near points of interest. It is important to note that Tesla Forecasting predicts point estimates as opposed to annual averages. While Tesla Forecasting uses elaborate regression models for electrical demand forecasting, they admitted that both of the other large companies in demand forecasting use neural network models.

2.3 Joint Perspective

The Air Force has generally used execution with adjustments made for inflation and recapitalization to build utility requirements. While historically using regression analysis for determining base operating costs [**?**, **?**] the Navy now uses an elaborate data collection and *price–demand* model to forecast utility requirements down to the facility type on any given installation. They collect intensity (MBTU/SF) data and then apply this to a list of known facilities square footage in order to get total consumption. This consumption is then multiplied by the Navy Working Capital Fund (NWCF) rate. The NWCF rate is the rate that Navy Facilities Engineering Command (NAVFAC) uses to charge customers for a given utility at a given location. This process is carried out inside the Heuristic Asset Management of Utilities Requirements (HAMUR) model which was developed by Booz-Allen-Hamilton. HAMUR is an automated web-based program which can forecast down to facility type using the simple formula

$$Cost = Quantity \times Rate$$

The complexity of this equation increases as the model takes into considerations various geographical locations and commodities. New footprints, demolition, energy efficiency investments, new/changing mission requirements, relocation of missions, level of service adjustments, and change in consumption behavior all have an inpact on quantity. Inflation, adjustments to balance the working capital fund, and level of service adjustments all impact the rate. Verification, validation, and accreditation of HAMUR will take place in fiscal year 2014. Electrical metering has been studied and increased in the Navy in order to support the HAMUR model as well as support other utility management decisions [Ackerman and Shaw, 2003].x

3 Documenting the BRM Process with *Electrical* Service

3.0.1 Installation Status Report

The BRM process begins with the collection of service level performance data at the installation level. This is done through the Installation Status Reporting–Services (ISR-S). ISR-S collects both performance measures and pacing measures for services. A performance measure is normally related to the quality of service. The number and length of time of electrical outages on an installation is an example of a performance measure, specifically measuring the quality of *electrical* services provided on an installation. Performance measures are used to determine a Green, Amber, Red, or Black quality rating. A pacing measure is a metric which accounts for most of the variance in the cost of the service. Annual mega-watt hours (MWh) used on Army installations is the primary pacing measure used for *electrical* services. The marginal cost of MWh assists us in understanding past execution as well as predicting future execution. Many services include both a primary and secondary pacing measure; the total population assigned to an installation is the secondary pacing measure for *electrical* services.

ISR-S data is either top-loaded from official databases of record or is entered by the respective installation. Population data is top-loaded from the Army Stationing and Installation Plan (ASIP) database, real property data is top-loaded from the Headquarters Installation Information System (HQIIS) database, energy data is top-loaded from the Army Energy and Water Reporting System (AEWRS) database, and financial data is top-loaded from Defense Finance & Accounting Service (DFAS) 218 and/or GFEBS. For all other data, installation, state, or Reserve Regional Support Command (RSC) managers enter requested performance measure data through a web interface (Installation Status Report, 2011).

3.0.2 Standard Service Costing

Standard Service Costing (SSC) is the process overseen by the Deputy Assistant Secretary of the Army for Cost and Economics (DASA-CE) by which parametric statistical relationships are established between potential cost drivers and historical execution. These cost-estimating relationships (CER) are then used to estimate future requirements. The SSC process begins by normalizing the data temporally and spatially. The cost data is normalized temporally by bringing all expenditures back to a base year dollars. The data is also normalized geographically to take into consideration the regional variance in cost of services. Once the data for a given service is normalized, analysts attempt to use single variable linear regression to establish a CER between the primary pacing measure and historical execution using three years of data. If the primary and secondary pacing measures do not yield a strong fit with historical execution, then other installation data (such as total population or total building square feet) are tested. Once a strong CER is established, the regression equation is used to predict in the out years. The prediction is then denormalized temporally and spatially and summed to identify the total requirement for a given service. This is then adjusted by the level of performance in order to generate a requirement at the Green, Amber, Red, and Black levels. This process is repeated for each component (Active, National Guard, and Army Reserve). If a strong cost-estimating relationship is not found (strong measured by R^2, or "goodness-of-fit," exceeding 0.4), then a two or three year average of historical execution is used for the service requirement.

Once an explanatory variable is selected and a given regression model built, analysts will use that model to predict the requirement for the out years. To do this, they first need to estimate the explanatory variable for the out years. If the explanatory variable, or cost driver, is a population measure (i.e. military population or total population) or real property (i.e. square feet) then these are generally estimated for the out-years in the databases of record, and these estimated values are used for prediction. If the pacing measure is not population or real property, then the given pacing measure is often adjusted by population. For electricity, MWh is adjusted by the estimated installation population in the out-years. The per-capita consumption of MWh is calculated for the last year of the historical data, and multiplied by the future estimate of population at a given installation in order to estimate the future usage of MWh, as is seen in the formula below:

$$Consume_{Future} = \frac{Consume_{Present}}{Population_{Present}} Population_{Future}$$

This estimate of MWh is then used to predict at the installation level. These regression predictions, however, are not generally used as the installation estimate. Rather, all of the installations estimates are summed in order to calculate the total component requirement (separately for the Active, National Guard, and Reserve), and ACSIM then uses the historical proportion to calculate the installation requirement.

Figure 11 through Figure 17 demonstrate the steps of Standard Service Costing (SSC).

3.0.3 Historical SSC Results

As seen below in Table 1, data from the Reserve and Active components have historically facilitated a CER with MWh as the cost driver. POM 1317 and 1418 deviated from this trend, arguably due to two actions: 1) the movement from DFAS to GFEBS and 2) the use of Overseas Contingency Operations (OCO) funding for base services. The National Guard has a much higher variance in their SSC Results, alternating between direct expenditure data or various cost estimating relationships. The most common CER used by the National Guard is Total Population. Note that, although the SSC Standard Operating Procedure (SOP) instructs analysts to explore multivariate regressions models, these multi-variate models have never been used for the *electrical* service.

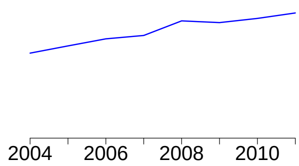
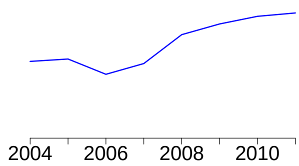
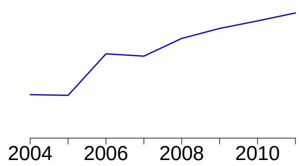
POM	Active	National Guard	Reserve
1418	2-Year Avg Adjusted for TotPop	2-Year Avg Adjusted for TotPop	CER-Total Pop
1317	CER-TotPop	CER-TotPop	CER-Total Pop
1216	CER-MWH	FY08 Expenditure	CER-TotPop or MWH
1115	CER-MWH	CER-Totpop	3-Yr Average
1015	CER-MWH	CER-TotPop	FY07 Expenditure
0913	CER-MWH	CER-TotPop	CER-MWH
0813	CER-MWH	3-Yr Avg	CER-MWH
0711	CER-MWH	CER-Linear Feet of Electrical Lines	CER-MWH
0611	CER-MWH	None Given	CER-MWH
Execution			

Table 1: Historical SSC Results for *Electrical* Services

4 Candidate Models

Our candidate solutions, listed in Table 2, fall into four broad categories. The first category is linear regression models. Using SSC as a baseline, we explored multiple changes to the current process. In particular, we spent significant time exploring multiple variate regression models based on our discussions with Tesla Forecasting Company. Additionally, we explored transformations to the response variable and robust weighted regression (iterative reweighted least-squares). The second category contains several solutions that separately model price and demand, putting the two results together in order to generate a requirement. This utilizes the *engineering approach* and is somewhat related to the Navy's HAMUR model. The third type of candidate solution is neural networks, which are not constrained by many of the assumptions of parametric statistical analysis. The final candidate solution we explored was the Principal Component Analysis Indexed method developed by the Center of Naval Analysis (CNA).

Table 2: Candidate Solution Models

Category	Models
Single Variate Regression	Baseline SSC Power transformation of response variable Single Variate Robust Weighted Regression
Multi-Variate Regression	Standard Multi-variate Regression Power Transformation of response variable Robust Weighted Multi-Variate Regression
Price–Demand	Using Time Series Analysis for Price Using Regression Analysis for Price
ANN	Neural Networks
PC Analysis	From Center for Navy Analsysis (CNA) Research

4.1 Simple Regression Models

Standard Service Costing has historically performed well for *electrical* services. The cost driver (MWh) is the direct item of purchase, and any variance in the model is primarily tied to regional differences in cost and pricing structures. Poor regression models are most often associated with inconsistencies and errors in the data. All regression models use the SSC methodology outlined in the main body.

Figure 5 provides a visual of the regression model using 2006, 2007, and 2008 data. Notice that the $Slope = \$71.0/MWH$, or $\$0.071/kWH$, which agrees with Department of Energy national averages. This model has strong "goodness-of-fit" given $R^2 = 0.85$. In this plot, installations from the Northwest and other lower energy cost regions are generally plotted below the trend-line, while installations from the Northeast and other high cost areas are plotted above the trend-line. We chose not to force the regression through the origin, though have been permissible with this data.

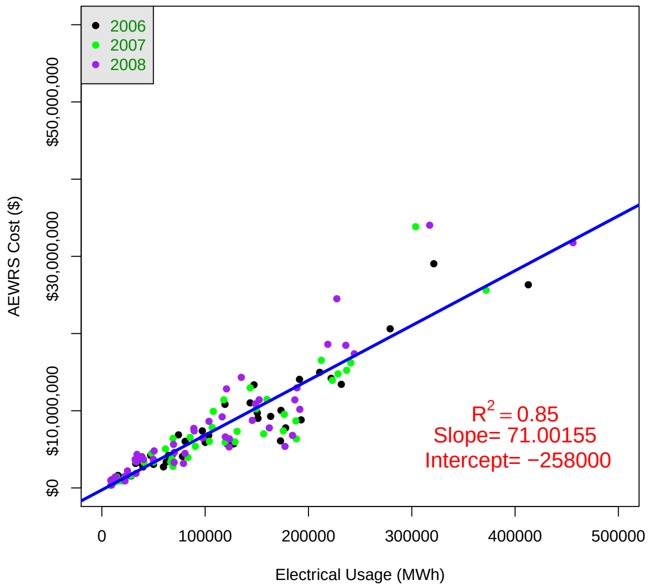


Figure 5: Historical Single Variate Regression(SSC) using 2006-2008 AEWRS Data

We primarily tested three types of single variate regression models. The first was the current SSC methodology without any changes. This model served as our baseline. The second regression model uses a power transformation of the response variable (MWh). All of the regression models we tested (both single and multi-variate) contained various degrees of heteroscedasticity and non-normal residuals. The heteroscedasticity and non-normal residuals are clearly evident in Figure 6. One method to fix heteroscedasticity and non-normal residuals is through a transformation of the response variable. We used the Box-Cox estimate of λ for Power Transformation, and found that $\lambda \approx 0.5$. The square root transformation of the response variable adequately corrected the heteroscedasticity and non-normal residuals in most of our regression models.

The final candidate model we tested used robust regression (also known as iterative reweighted least-squares regression) in order to decrease the influence of outliers. In order to do this we used *M-Estimation* and iteratively reweighted least-squares (IRLS), which was introduced by Huber (1964). A full explanation of robust regression is beyond the scope of this paper.

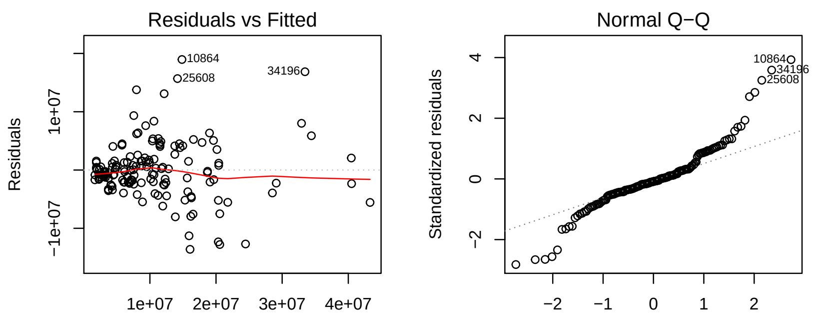


Figure 6: Heteroscedasticiy and Non-normal Residuals as seen in regression models

4.2 Multi-Variate Regression

Multivariate regression attempts to add other explanatory variables to the regression model. These variables include population data, real property data, and weather data (in addition to megawatt-hours). Most of these variables are included in the ISR data set, with the exception of weather data.

Given the large amount of literature addressing the use of weather variables in electrical load forecasting, we decided to merge weather variable with the ISR data set. The two primary variables we added were *Heating-Degree-Hours* and *Cooling-Degree-Hours*, since these assist in determining the energy intensity required for heating and cooling, respectively. Weather data was collected from the National Oceanic and Atmospheric Administration (NOAA). We developed a script in *R* that would automatically geocode Army installations, find the closest relevant weather station that NOAA monitors, download the detailed weather day for that station for the years of interest, calculate the *heating-degree-hours* and *cooling-degree-hours*, and finally merge this new data with the ISR data set. We calculated *heating-degree-hours* by establishing the base comfortable temperature at 20 degrees Celsius and summing all hourly deviations that are less than 20 degrees with

$$\sum_{i \in \{Temp_i < 20^\circ\}} 20^\circ - Temp_i$$

We calculated *cooling degree-hours* by once again establishing the base comfortable temperature at 20 degrees Celsius and summing all hourly deviations that are greater than 20 degrees with

$$\sum_{i \in \{Temp_i > 20^\circ\}} Temp_i - 20^\circ$$

These summations were conducted for each installation and each fiscal year in the time horizon of interest, and then merged with the ISR data set where it was readily available for use in multi-variate regression. Additionally, we added the latitude of each respective installation as another possible explanatory variable.

In order to determine the strongest multi-variate regression model (i.e. the model with the best variables selected based on statistical fit), we placed all potential variables into a regression model and used stepwise model selection by Akaike Information Criterion (AIC). For *electrical* services, we started by building the following regression model:

$$Cost \rightarrow \beta_0 + \beta_1 MWh + \beta_2 Enlisted + \beta_3 Officer +$$
$$\beta_4 CivPop + \beta_5 TotalAcres + \beta_6 LaneMile + \beta_7 Sqft +$$
$$\beta_8 FamQrtrs + \beta_9 Barracks + \beta_{10} HHours + \beta_{11} CHours + \beta_{12} Lat$$

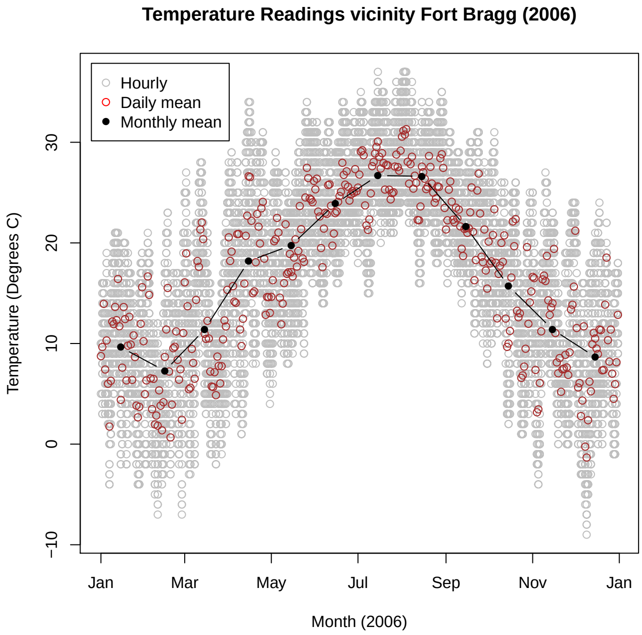


Figure 7: Hourly NOAA Weather Data for Fort Bragg (2006)

Using forward and backward step-wise model selection using AIC, we found that MWh, population data, Heating-Degree-Hours, and Latitude were generally included in the multi-variate model due to their statistical significance.

Like single-variate regression, we tested a baseline model, as well as a model that conducted a power transformation of the response variable and a robust multi-variate regression.

Multi-variate regression using physical property and population data as explanatory variables raised some concerns about independence of the explanatory variables. Least squares linear regression assumes independence of the explanatory variables. Many of our variables do have some degree of correlation, however. For example, if an installation has high real property square footage, it will tend to have a high population. A lack of independence among explanatory variables is known as multicollinearity. Many statisticians use the Variable Inflation Factor (VIF) to measure the severity of multicollinearity found in a least squares regression model. VIF factors greater than 10 indicate that a model has serious multicollinearity concerns. [Montgomery et al., 2006] Table 3 shows the variable inflation factors for the Active Component *Electrical* services multi-variate regression model. Note that several of our variable are high, though none of them exceed the 10.

Explanatory Variable	VIF
MWh	9.77
Sqft	7.45
Officer Population	3.72
Heating-Degree-Hours	3.61
Latitude	3.64

Table 3: Variable Inflation Factors for the Active Component multi-variate regression model

4.2.1 Price–Demand Model

While analyzing *electrical* services, we acknowledge that different factors affect the unit price and consumption of *electrical* services. Economic, energy policy and various other factors affect the unit price of electricity, while population, real property, energy programs, and weather affect the consumption/demand for electricity. In a model that we called the *Price–Demand* model, we separately model price and demand at installation level using the following equation:

$$Demand \times Price + CivPay = Requirement$$

We tested time-series and single variate regression models for price, and multi-variate regression models for demand.

We tested five time-series forecasting models for use in modeling an installation level unit price for electricity. We used double moving average, simple exponential smoothing, double exponential smoothing, auto-regressive integrated moving average (ARIMA), regression, and "blind" inflation. We used each of these models on annual energy price data across the United States, produced predictions, and compared the predictions to actual price data. Among the ARIMA family of models, we used an ARIMA(0,2,2) model. We then compared the models using mean absolute error (MAE). The results are given in Table 4. Exponential smoothing (without trend) has the lowest mean absolute error and was used to predict price. The fact that the final model is very conservative and does not contain a trend is evidence of the high volatility of energy prices over the last twenty years. Discovering high variability in this installation level

	Mean Absolute Error
Exponential Smoothing	0.65
Inflation	0.72
Regression	0.86
Double Moving Average	1.01
ARIMA	1.06

Table 4: Mean Absolute Error (in cents) for Price Forecasting Models

model, we also attempted a robust global model that simply used the slope of the regression of $Cost \rightarrow MWh$. This is arguably the fully loaded marginal price of a MWh for the Army. This is the model we actually used and is represented in our results, since we found that the time-series analysis was very sensitive and could produce large errors at times.

We used multi-variate regression to model demand using the same step-wise model selection methods outlined above. In this case, demand instead of cost is the response variable. When this model was applied to the 2006-2008 Active Component ISR data, the step-wise AIC process selected population, building square-footage, installation acres, number of barracks, and latitude as explanatory variables.

4.3 Neural Networks

Artificial Neural Networks, based on their biological counterparts, have increasingly been used as an alternative for regression analysis. Neural networks are adaptable to many types of data and are not constrained by any of the underlying assumptions of regression. Their biggest drawback for requirements determination is that they are a "black-box" that decision makers, installations, and analysts may struggle to fully grasp and communicate. Neural network analysis is offered as a candidate solution for *electrical* services as a point of comparison. For this research we used neural network with a single hidden layer.

4.4 Principal Component Model

The Center for Navy Analysis conducted a recent study looking at higher level requirements generation models for the Navy. They propose using Principal Components Analysis to generate an index that measures the relative size of installations in respect to a given service. Their index

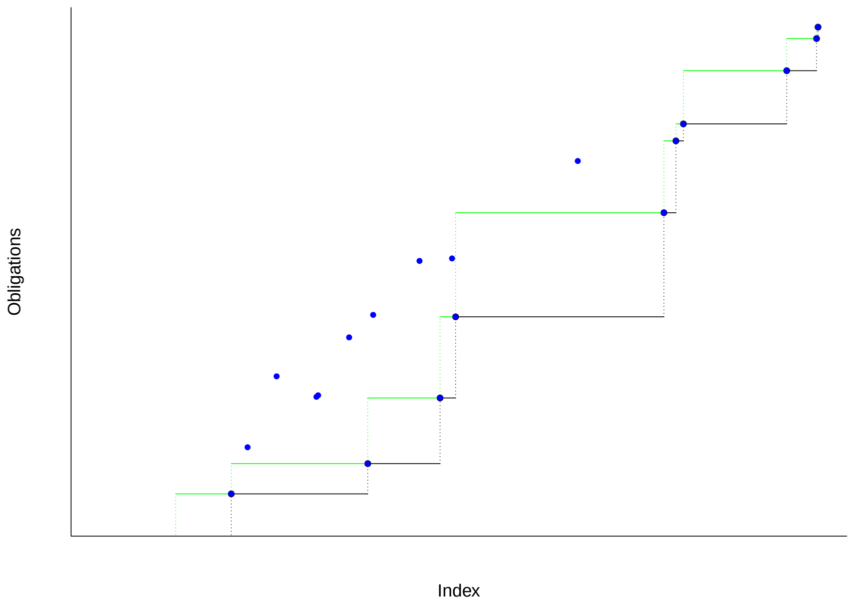


Figure 8: Replicate of CNA Principal Component Index Model [Davis et al., 2012]

is normalized so that it falls between 1 and 100. Using *Electrical* as an example, if installation A has a higher index than installation B, it means that in term of *Electrical* services, installation A is larger and should have a larger requirement. The Principal Components Index was calculated with many different variables that were determined to have a statistical significance for the service (similar to a multi-variate regression model). Only the first principal component is used for the index. Once the index for each installation was determined, they were plotted against historical execution. Rather than using least-squared linear regression to produce the trendline for predictions, however, they plotted a line along the lower boundary of the data which they then called the "efficient frontier," as seen in Figure 8. They argued that the installations on the lower boundary were the most efficient installations, and requirements should be based on the most efficient installations [Davis et al., 2012]. This methodology assumes perfect data and assumes the principal component generated index perfectly measures the relative size of installations in terms of a given installation service. Using this for Army *Electrical* requirement, we found neither the data nor the model facilitated a viable candidate solution.

5 Results

We compared candidate solutions quantitatively and qualitatively. Quantitatively we compared model predictions using historical data with actual electrical execution. We conducted qualitative comparison using ACSIM model criteria.

5.1 Quantitative Comparison of Models

We compared candidate models quantitatively with three runs through historical data and then compared model results to actual known execution. For example, our first run used historical data from 2004 through 2006 to run the models and then compared model results to 2009 execution data. Table 5 shows the details for all three of the runs . This type of comparison is appropriate for electrical services since it is a "must pay" utility that is marginally impacted by policy. We do not recommend this type of quantitative comparison for services with are highly sensitive to Army Policy, such as Custodial Services. In these cases, other quantitative measures were established.

Years for Data	Prediction and Comparison Year
2004-2006	2009
2005-6007	2010
2006-2008	2011

Table 5: Details for three iterations through historical data

Figure 9 provides percentage error for each model for all three iterations. Robust weighted regression out-performed related regression models in all cases (i.e. robust SSC outperformed legacy SSC and robust multi-variate regression outperformed standard multivariate regression). In general, multi-variate regression outperformed single variate regression with the exception of the last iteration. Neural Networks only provided marginal improvements over multi-variate regression. We found that using a power transformation, while reducing heteroscedasticity and non-normal residuals, produced greater prediction errors than any of the other candidate models. Although the *Price-Demand* model performed well for the first iteration (2009), in general it did not perform as well as expected. We also should note that all errors are positive. This is due to the fact that the DoD inflation factor used for all models was higher than actual realized electrical inflation for these years.

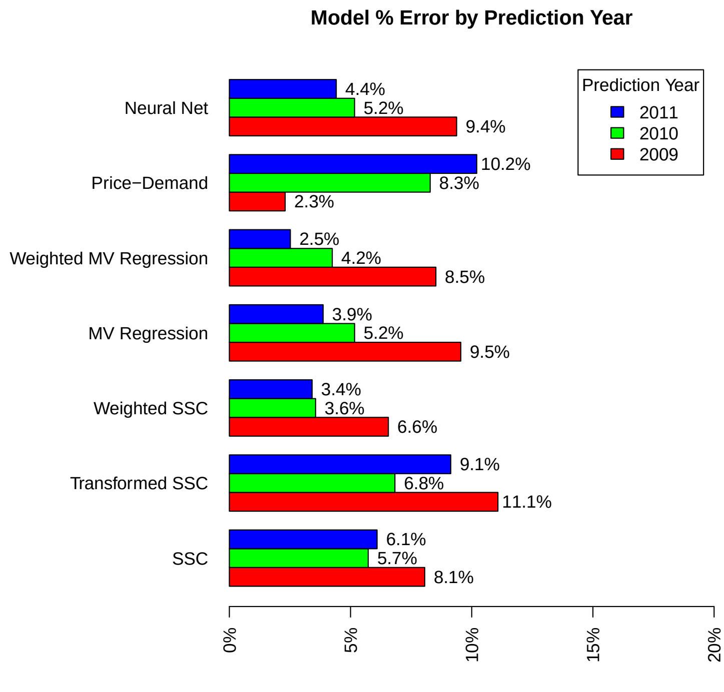


Figure 9: Comparing Model Results with 2011 Execution

In addition to comparing errors at the aggregate component level, we compared estimates at the installation level of detail. Table 6 shows the quantitative comparison of errors for the Active Component. Mean Squared Error (MSE) is the sum of the square of errors

$$MSE = \frac{1}{n}\sum_{i=1}^{n} Error_i^2$$

which inherently penalizes larger errors. Mean Absolute Error (MAE) is the sum of the absolute value of the errors

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Error_i|$$

and is measured in actual dollars. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Error_i|}{Execution_i}$$

measures the error with a view toward the size of the post. An error of $\$1,000,000$ is much different for a small installation than a larger installation. For this reason, MAPE was the primary metric of comparison, since it scales to the size of the installation.

	MSE	MAE	MAPE
SSC	1.58E+15	$3,159,093	55%
Weighted SSC	1.56E+15	$3,172,241	56%
MV Regression	1.07E+15	$3,043,037	56%
Neural Net	1.06E+15	$2,999,389	57%
Weighted MV Regression	1.30E+15	$3,126,496	58%
Price-Demand	1.53E+15	$3,499,879	60%
Transformed SSC	2.49E+15	$3,705,837	61%

Table 6: Quantitative Assessment of Candidate Solutions

As seen in Table 6, single variate regression (SSC) outperformed all other models at the installation estimate. Figure 10 demonstrates SSC (distributed by proportion of historical execution) for the Active Component. In this figure, the black data points are 2011 Execution at installation level, and the green data points are the model prediction (using 2006-2008 data). Notice that the errors grow in size with the larger installations. This growth of errors proportional to the size of the post is evidence of the underlying heteroscedasticity. Notice that Fort Hood produced the largest error. Fort Hood was the largest error for every model. This is primarily due to the 4th Infantry Division leaving Fort Hood during this time frame as well as high volatility of electrical prices (prices started at roughly $0.05 per KWh in 2005, rose to $0.10 by 2008, and then fell back down to roughly $0.05 in 2011).

5.2 Qualitative Comparison of Models

In addition to quantitatively comparing models, we qualitatively compared them based on the value measures created by ACSIM. These value measures are compared in Table 7. Note that the regression models tend to have more of the qualitative measures that ACSIM values. The *Price–Demand* models struggled with accuracy due to the difficulty of using time series analysis to estimate the installation level price of electricity. Additionally, the *Price–Demand* model required more data and time for the time-series analysis. The neural network model, while based on industry standards and marginally outperforming multi-variate regression analysis, lags behind in the qualitative assessment due to its "black-box" nature.

6 Conclusions and Recommendations

AEWRS cost and consumption data was far more reliable than ISR data in the years of interest that we studied. AEWRS measured the direct non-reimbursable portion of both cost and consumption that should be modeled for requirements generation. Since AEWRS is maintained

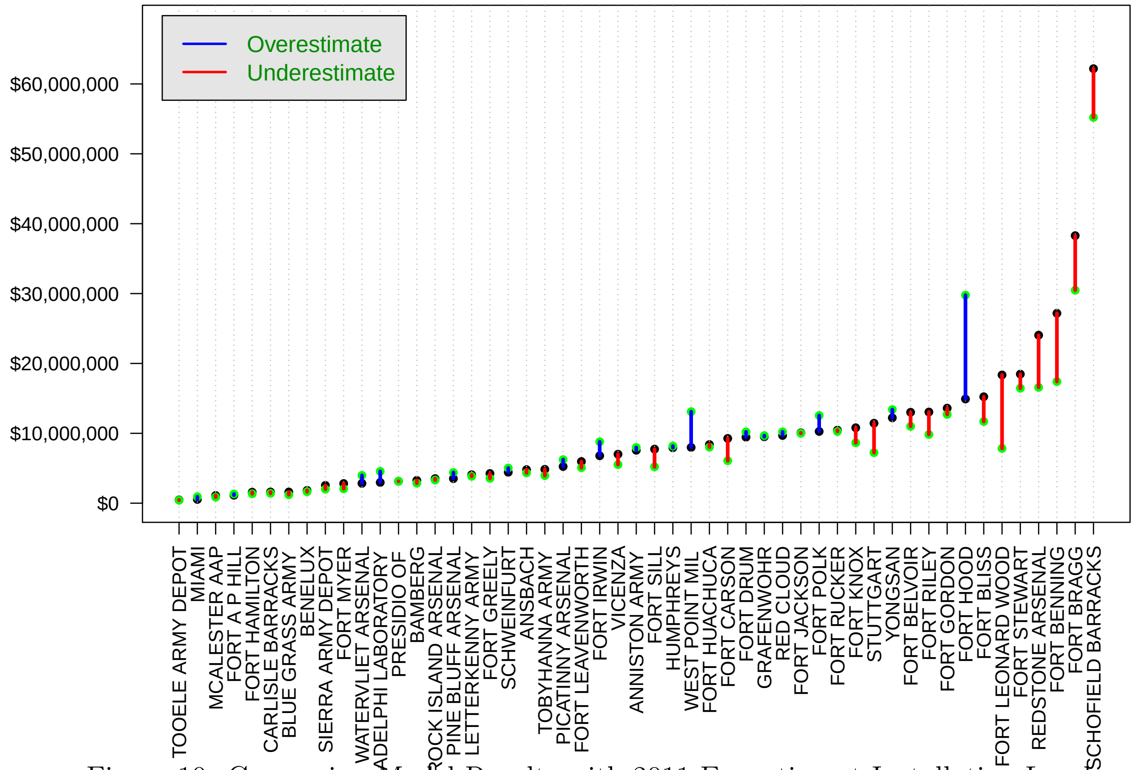


Figure 10: Comparing Model Results with 2011 Execution at Installation Level

by the actual energy managers at each installation, there is more quality control on data entry. AEWRS data is also available at monthly increments which is helpful for some modeling approaches.

Analysts should use robust weighted regression for the requirement generation of electrical services. While the SSC standard operating procedures briefly discusses methods to reduce the effects of outliers, these efforts are time-consuming and contingent on the expertise and patience of the analyst. Robust weighted regression reduces the work-load, is accurate, and is not contingent on the expertise or patience of the analyst.

Single-variate regression should remain the primary model for *electrical* services; however, analysts should spend some additional effort exploring multi-variate regression models. While the SSC standard operating procedure currently recommends this exploration, our study has never found evidence of a multi-variate model being used for requirement generation. These multi-variate models can provide greater accuracy and scalability.

Although Congressionally-mandated energy reduction policy was not included in this analysis, analysts should consider it during the requirements generation process as a method to assist in enforcing energy reduction laws.

Deployments can have a significant impact on an installation's energy usage, but deployments are difficult to measure and portray in current installation population data. All personnel data sources that we analyzed only reflect *authorized* personnel numbers, but not "boots on the ground." This "boots on the ground" data could provide greater understanding of the variance in installation consumption of electricity.

Steps of Standard Service Costing (SSC)

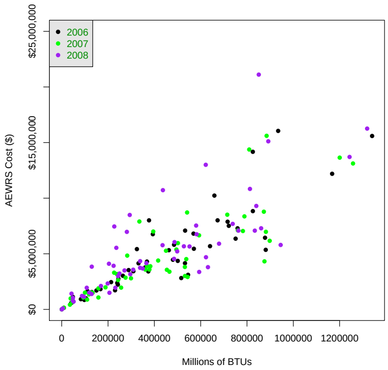


Figure 11: Initial Plot of Data

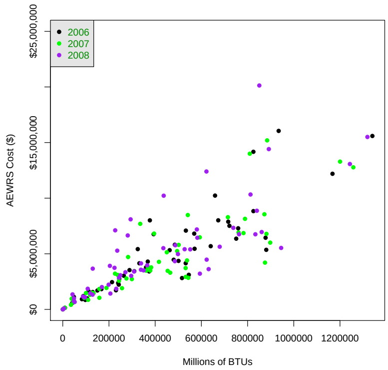


Figure 12: Normalize Data (Spatial and Temporal)

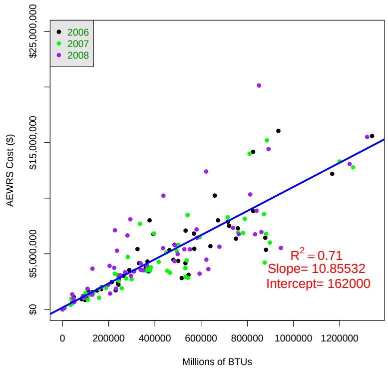


Figure 13: Create Regression Model

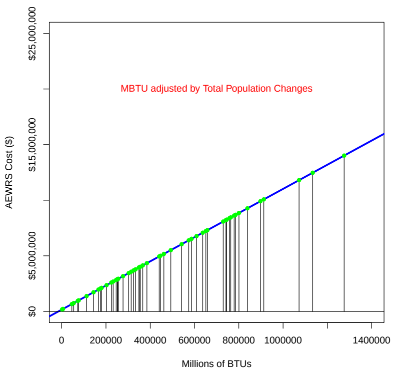


Figure 14: Predict with Population Adjusted Explanatory Variable

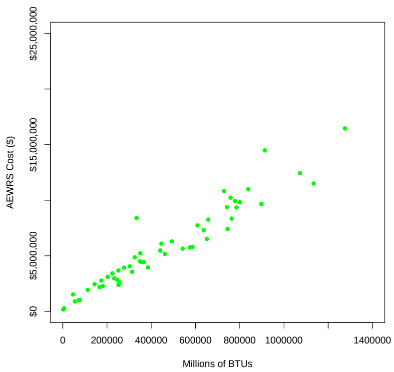


Figure 15: Denormalize Results

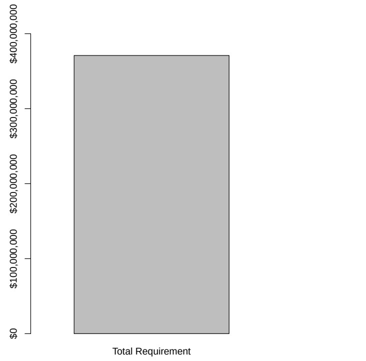


Figure 16: Sum total requirement

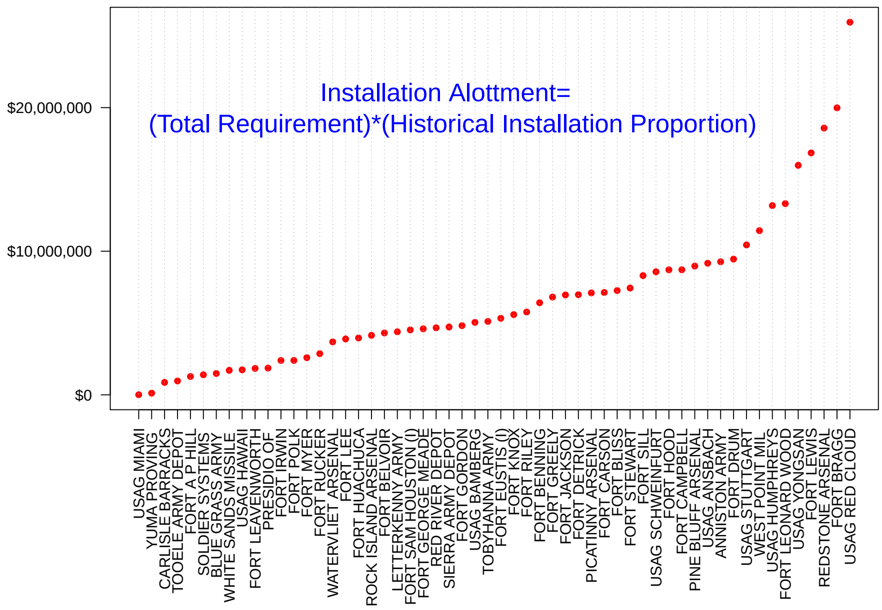


Figure 17: Create installation distribution based on historical execution

Qualitative Value Measure	Regression	Price-Dem	Neural Net
Accurate	3	2	3
Scalable	3	3	3
Distinguishable critical & competing	3	3	2
Minimizes workload	3	2	3
Consistent	3	1	3
Applicable (CMD, APPR, MDEP, PE)	3	3	3
Risk Aware	3	3	3
Outcome Based	3	3	3
Tailored for Service	2	3	2
Confirmable	3	3	3
Repeatable	3	3	2
Databases of Record	3	3	3
Official or Industry Standard Cost Rates	2	2	2
Manpower Informed	3	3	3

Table 7: Qualitative Value Measure Assessment

Acronyms

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Table 8: Acronyms

DASA-CE	Deputy Assistean Secretary of the Army -Cost/Economics
POM	Program Objective Memorandum
PBR	Pre-Budget Report
ISR-S	Installation Status Report-Services
GFEBS	General Fund Enterprise Business System
MDEP	Management Decision Package
ORCEN	Operations Research Center
IMCOM	Installation Management Command
MWh	Millions of watt-hours
MMBTU	Millions of BTUs
ASIP	Army Stationing and Installation Plan
HQIIS	Headquarters Installation Information System
AEWRS	Army Energy and Water Reporting System
DFAS	Defense Finance & Accounting Service
RSC	Regional Support Command
PSC	Primary Service Category
PM	Performance Measure
DoD	Department of Defense
MILCON	Military Construction
OSD	Office of the Secretary of Defense
PE	Program Element
ARF	Army Resource Framework
GPRA	Government Performance and Results Act (1993)
MID	Management Initiative Decisions
TAADS	The Army Authorization Document System
BASOPS	Base Operations
CNIC	Commander, Naval Installation Command

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