Quantitative Approach to Select Energy Benchmarking Parameters

For Drinking Water Utilities

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ABSTRACT

Energy efficiency is currently a hot topic on all regional, national, and global stages. Accurate measurements on how energy is being used over a period of time can improve performance of the drinking water utility substantially and reduce energy consumption. Nevertheless, the drinking water industry does not have a specific benchmarking practice to evaluate its energy performance of the system. Therefore, there are no standards to compare energy use between water utilities that have a variety of system characteristics. The goal of this research is to develop quantitative approach to select energy benchmarking parameters of the water system, so the drinking water utilities can use those parameters to improve their energy efficiency. In addition to a typical benchmarking of drinking water utilities, the energy benchmarking can specifically compare energy efficiency of a utility with other utilities nationwide.

The research developed a regression model based on the statistical representation of the energy use and descriptive characteristics of the drinking water utilities data throughout the U.S. Methodologies to eliminate singularity and multicollinearity from collinear survey dataset are discussed. The all possible regressions were chosen as parameters selection methodology to identify a subset of most significant parameters, i.e. system characteristics, that can mathematically correspond to energy use across different utilities. As a result, the energy benchmarking would be able to calculate the predicted total energy use of the system from given system characteristics.

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CHAPTER 1. INTRODUCTION

1.1 Water and Energy

Water and energy had been generally treated as two separate issues. However, water and energy existences, known as water energy nexus, were closely related and mutually dependent resources (NCSL 2009). With the current impact from the climate change, there was a need to thoroughly understand the relationship between water and energy (Cabrera et al. 2010). The water infrastructure demanded vast amount of energy, and energy production also required countless volume of water. Therefore, a sustainable management of water would be largely depended on energy and vice versa.

In the United States, there were more than 52,000 community water systems according to the U.S. Environmental Protection Agency (U.S. EPA) (2007). In those 52,000 systems, only 4,000 systems had serving population over 10,000 people, and they accounted for approximately 85% of the whole U.S. population. Water and wastewater utilities together consumed roughly 3% of total U.S. electricity use. Many drinking water facilities throughout the nation had the energy costs as the second highest, only second to the labor costs, of their annual operational budget according to the U.S. EPA (2009).

There were many factors that affected the cost and amount of energy usage. Those factors were associated with regulations, aging infrastructure, growth, treatment technology complexity, and supply challenges (ISO 2005). In addition to its standard of high-priority concerns, the water supply system also faced the increased health and environmental related regulatory requirements. For example, the higher requirement of the drinking water standard mandated to have additional treatment such as the disinfection of microbial contamination (Liu et al. 2012). Such a treatment required installations of high energy-intensive technologies.

Federal and States throughout the nation had searched for opportunities to reduce the energy demand associated with the water supply system during peak hours. Ways to decrease the energy use for operating water transportation and treatment systems were also in high demand.

1.2 Energy Efficiency in Water Utilities

Energy efficiency had been on agenda of most governments in the developed countries around the world, especially for public policy and energy sustainability issues (Patterson 1996). The increases in energy efficiency would promote industrial competitiveness, energy security, and environmental surroundings.

Improving water efficiency was directly equivalent to improving energy savings because the less energy would be used in the process such as pumps, thus it extended the service life of treatment equipment and parts. Also, the financial savings resulted from fewer needs of chemicals and other treatment materials (Leiby and Burke 2011). Thus, improving energy efficiency was a vital step to reduce expenses for water utilities.

There were many opportunities that could help water utilities to reduce their energy consumption. Implementing the energy efficiency practices would yield significant cost savings. Furthermore, the activities such as optimizing current treatment, pumping, and operational practices could be executed within a restricted budget.

At this moment, there were inadequate consideration on how to define and measure the energy efficiency. Therefore, ways to evaluate how energy was being used over time can significantly improve not only energy management but also performance of the whole system (NYSERDA 2010). There were many tools that utilities could use to measure their total energy consumption throughout the process of production, treatment, and distribution. The energy benchmarking was one of the highly regarded approaches recommended by Water Research Foundation (2007).

The energy benchmarking could be an effective tool to compare the energy use of a utility with the national average after normalized different utilities' characteristics and operational functions. The energy benchmarking result could be a good indicator that reflected the energy efficiency in a water utility. In fact, the energy benchmarking could provide drinking water utilities measures to improve their energy efficiency and serve as an initial step in the utility energy management.

1.3 Goal and Objectives

1.3.1 Goal

The goal of this research is to improve energy benchmarking practices in drinking water utilities. It would help to improve existing practices on how to measure and select energy benchmarking parameters. Therefore, the utilities can use those parameters to improve their energy efficiency.

The research scope covered the entire drinking water system including water transmission, treatment, storage, and distribution.

1.3.2 Objectives

The study had three objectives as followings.

1. Identify the critical energy parameters to support the energy benchmarking
2. Develop the mathematical analysis to select energy parameters

3. Recommend ways to improve the current benchmarking practices and create national online database

CHAPTER 2. LITERATURE AND PRACTICE REVIEWS

2.1 Energy Benchmarking in Drinking Water Utilities

The definition of benchmarking is “a continuous, systematic process for evaluating the products, services, and work processes of organizations that are recognized as representing best practices for the purpose of organizational improvement” (Spendolini 1992). In other words, benchmarking was to compare performance metrics between one’s own organization with the best practices of similar organizations in the industry, described by Water New Zealand (WaterNZ) (2012). Below were the general benchmarking procedures:

1. Identify issues by metrics
2. Collect internal data to establish baseline
3. Compare data with peers
4. Analysis the system
5. Implement and monitor changes

Benchmarking in the water infrastructure system could not measure just the performance, which most of all existing benchmarking focus on. The current performance benchmarking metrics, both physical and functional, had no specific consideration of energy. There were, in fact, very limited sets of standard for energy benchmarking in drinking water utilities.

From the literature and practice reviews of major water institutions worldwide, there were very few water benchmarking that had energy parameters dedicatedly to measure the energy efficiency in the water utilities. Out of the 16 benchmarking reports in the Table 1, there were only five that had metrics specifically for evaluating energy performance.

TABLE 1: EXISTING ENERGY BENCHMARKING IN WATER UTILITIES

Institution & Title / Metrix Category			General Information	Coverage & Quality of Service	Customer Service	Finance	Human Resources	Environment and Health	Natural Resource Management	Assets	System Operation and Maintenance	Electrical Systems	Metering and Billing	Energy	Miscellaneous	Total Metrics
#	Institution (Year)	Title	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Agricultural Water Management, Elsevier (2010)	Management Evaluation of Water Users Associations Using Benchmarking Techniques	√	√		√		√			√			√		102
2	American Water Works Association Research Foundation (AwwaRF) (2007)	Energy Index Development for Benchmarking Water and Wastewater Utilities	√	√				√		√	√			√		194
3	European Benchmarking Co-operation (2011)	Water and Wastewater Benchmark Learning from International Best Practices		√	√	√				√			√	√		13
4	Indian Ministry of Power & International Finance Corportation, World Bank Group (2008)	India Manual for the Development of Municipal Energy Efficiency Projects						√			√	√				24
5	Intergrating Water Systems: Computing and Control for the Water Industry (2010)	Towards the improvement of the efficiency in water resources and energy use in water supply systems						√	√							8
6	Local Government Association of NSW & Department of Primary Industries Office of Water, Australia (2013)	2011-12 State of New South Wales Water Supply and Sewerage Benchmarking Report		√		√		√	√		√		√			54
7	Pacific Water and Wastes Association (PWWA) (2012)	Development of a Water Utility Benchmarking System	√	√	√	√	√	√		√	√				√	234
8	The International Benchmarking Network for Water and Sanitation Utilities (IBNET) (2011)	The IBNET Water Supply and Sanitation Performance Blue Book		√	√		√		√	√	√		√			91
9	The International Water Association (IWA) (2011)	Benchmarking Water Services : Guiding Water Utilities to Excellence		√		√	√	√		√	√					166
10	The South East Asian Water Utilities Network (SEAWUN) and the Asian Development Bank (ADB)	SEAWUN Benchmarking Survey for 2003 'Data Book' of data and results	√	√	√	√	√			√	√					158
11	The Water and Sanitation Program (WSP), The World Bank (2010)	Benchmarking for Performance Improvement in Urban Utilities: A Review in Bangladesh, India, and Pakistan		√			√		√		√		√			7
12	The Water and Sanitation Program, The World Bank (2009)	Water Operators Partnerships Africa Utility Performance Assessment	√	√	√	√	√		√	√	√		√			47
13	United States Agency International Development (USAID) & US Department of Energy (2010)	Benchmarking Energy Consumption in India Data Centers									√	√		√		30
14	Vewin by Accenture Nederland, Netherlands (2009)	Reflections on Performance Benchmarking in the Dutch Drinking Water Industry		√	√	√		√			√			√		51
15	Water New Zealand (2012)	2011/2012 National Performance Review of Water Utilities	√		√	√		√		√						63
16	WSP, UN Habitat, IWA- East and Southern Africa Region, African Water Association (AfWA) (2009)	Water Operators Partnerships Africa Utility Performance Assessment	√	√	√	√	√			√			√			28

The current benchmarking practices are very lengthy with hundreds of parameters. Lots of existing parameters had overlapped each other. They were time-consuming and complicated process. Nonetheless, these benchmarking metrics could not reflect the actual energy efficiency of the drinking water utilities. There were no direct correlations to be able to measure the system energy performance effectively. Then, there was a need for better sets and meaningful standardized of benchmarking parameters (Brueck et al. 2003) that were more concise and accurate, so the new sets of benchmarking would reduce confusion and deliver maximum information within a timely manner.

More importantly, the benchmarking results might serve as the initial baseline for all improving efforts (WERF 2009). With compelling ideas from the results, the plant operators would be able to identify areas where energy efficiency improvement should be executed and know how much they could be improved. By comparing information of energy use with other utilities, energy benchmarking was good for both encouraging improvement and sharing properly identified best practices (Liu et al. 2012).

2.2 Potential Ways to Improve Energy Efficiency in the Drinking Water Utilities

2.2.1 Management Tools

The management tools could provide a better understanding of the current utilities' energy consumption and be used to define the intensive-energy-used area within the system. They could set goals, define energy conservation measures, prepare implementation process, and monitor the improvement (Leiby and Burke 2011).

2.2.1.1 Benchmarking:

The designed metrics of energy benchmarking would help drinking water utilities to compare their energy use. According to WaterRF (2011), the goals of benchmarking were to have performance measurements in all areas of production, treatment, and distribution on energy related consumption of the drinking water and utilities such as total flow, raw pumping horsepower, distribution elevation change, etc. The data would be used to track changes and improvements internally and to compare externally with other utilities in the industry.

Examples of benchmarking tools:

1. USEPA's Energy Star Portfolio Manager
2. USEPA's Energy Star Cash Flow Opportunity Calculator V 2.0.

2.2.1.2 Energy Audits:

The energy audit was one of the means that would allow the utilities to evaluate the whole system and to locate sections and opportunities for energy efficiency improvement without having negative impact system performance and water quality. Since the pumping of raw water to distribution and treatment process accounted for roughly 80 percent of the energy use in the drinking water plants, the plant operator would need to have energy audits to manage and assess energy consumption of the utilities, a study by Leiby *et al.* (2011). The energy audits would spot the most energy-intensive areas within the system and plan a series of potentials energy conservation activities.

Generally, there are two types of energy audits. They are a "high-level" or a comprehensive "detailed process." A high-level or walk-through energy audit is typically performed to evaluate the most energy-use intensive component or other key problem areas of the system. It would dictate when and where the detailed process energy audit should be performed. The detailed process audit concentrated on the assessment of a certain area or operation identified by the high-level audit. In doing so, it would offer a comprehensive understanding and possible improvement regarding to that issue. Common focal points for executing a detailed process energy audit would be raw water pumping, distribution system pumping, filtration, and treatment processes. An energy inventory could be created from data gathered during the energy audit. Moreover, the information from the energy audit and energy inventory would help the utilities staffs to develop an energy map.

The processes of performing both high-level and detailed process audit were fairly similar, but the difference was in the detail of data collection. The detailed process audit would concentrate on a particular component or operation while the high-level audit focused on the overall system. Below was an energy audit process outline as described in the Electric Power Research Institute (2011):

- Holding a kickoff meeting
- Creating a team of water utility staff, electric utility personnel, and outside experts
- Collecting plant or specific operational process data, whichever is applicable for the type of audit being performed
- Evaluating electric bills and electric rate schedules
- Conducting field investigations and holding discussions with operations staff
- Creating an equipment inventory and distributions of demand and energy
- Developing energy conservation measures and strategies
- Following up on implemented measures

Energy and Water Quality Management Systems:

The Energy and Water Quality Management Systems (EWQMS) was a model developed by Water Research Foundation (WaterRF), Electric Power Research Institute (EPRI), and eleven of the largest water utilities in the United States (WaterRF 2012). Even though EWQMS was a generic model, it could be adjusted to suit a particular utility. With certain input information of a specific utility, the EWQMS could provide a framework and execution plan to minimize energy costs while still sustaining water demand and quality within the operational constraints and limited resources. Thereby, the utility would have a specific plan stating how it should be functioned and what can be anticipated, if operated accordingly.

The WQAMS was a sequence of separate application software application and operational practices that could deliver flexible planning and scheduling maneuvers to resolve water quality and energy management difficulties (Leiby and Burke 2011). In general, the operation of EWQMS was accompanied by a utility Supervisory Control and Data Acquisition (SCADA) system. The EWQMS would receive data from and give commands to a SCADA system to operate components of a utility such as pumps and equipment at treatment facilities and distribution systems (WaterRF 2012). All in all, the benefits of EWQMS might include energy efficiency and water quality improvement, cost savings, revenue increase, etc.

2.2.2 Plant improvements and management changes

To maximize the benefits of energy efficient improvement, drinking water and wastewater utilities should implement improving measures on the whole process not just a particular operation/treatment process. The typical facility-wide utility improvements involved lighting and heating, ventilation, and air conditioning (HVAC) upgrades for facility plant, ground, and building. These improvements could be achieved easy and have no impact to the normal utility operations. Also, installation of electric and natural gas submeters could give considerable savings to the utility, yet the implementing expenses could be compensated if associated with installing new utility equipment. The industrial trend was moving toward the use of an automatic control system such as Supervisory Control and Data Acquisition (SCADA). Recommendation by WaterRF (2011), the utility might apply for incentives and rebates to reduce the financial impacts from electric providers and other government agencies like New York State Energy Research and Development Authority.

Some challenges the water utility faced were related to the management changes that they had to do with changing/modifying typical ways of decision makings to promote new policy or procedural amendments. A water utility, and the local authority that owns the system, might have to thoroughly prioritize measures of energy efficiency improvements. It also had to analyze where and how to implement those measures considering its technical and financial competences. As a result, the prioritization would allow the utility not only to reach its energy reduction goals but also maximized its potential savings (Leiby and Burke 2011).

2.2.3 Water Treatment

Because of changing water quality regulations such as disinfection byproducts and micro-biological inactivation as well as higher expectation of water quality from consumers, a water utility had to adapt new treatment/disinfection technologies rather than using conventional treatment. Those commonly founded treatment were coagulation, sedimentation, filtration with choline disinfection. Generally, treating surface water systems accounted for 10 to 20 percent of the total energy costs according to WaterRF (2011), which the rest would be used for pumping water from sources to the treatment plant and from plant to the end-users. Therefore, the biggest potential energy savings would be in the distribution sector, yet many utilities saved significantly in optimizing treatment.

The new standard on water quality would inevitably drive the water utility to acquire newer technologies. For example, those new and energy-intensive technologies were reverse osmosis and desalination. The utility might be able to solve energy problems by finding alternative approaches. A drinking water plant, for instant, was located next to a river where it could adapt riverbank filtration instead of using flocculation, sedimentation, and filtration processes but disinfection (Leiby and Burke 2011).

It was very important for water utilities to be realistic and set achievable goals based on their competencies; they had to carefully select treatment process/technologies that would be best for the whole system optimization. Methods such as life cycles costs, payback, and overall benefits of economics input-output life cycle assessment could help water utilities to evaluate each improving option. Some implementations might result in considerably higher energy savings than others. However, the whole system optimization approach could be accomplished with the right combination between the technology and other energy improvements. It would yield overall energy reductions that have greater savings compared to each individual implementation.

2.2.4 Water Distribution

In the USA, the water industry used roughly around 3% of total electricity production, and up to 90% of this 3% total electricity was consumed by pumps (Bunn and Reynolds 2009). Water was comparatively liquid. It weighted round 62.4 pounds per cubic feet or 8.34 pounds per US gallon. The energy efficiency improvements in the water distribution system had two main approaches. First was enhancing the efficiency of generating water pressure, and second was reducing in amount of water pressure demand.

Optimization of the complete water distribution system including pipes, storage, valves, etc.—which can lead to resize pump capacities and the total number of pumps accordingly—could facilitate energy needs to pump water. A large capital investment was not always necessary to implement the system efficiency improvements or total energy reductions, often it was not required at all. A vital tool to evaluate energy efficiency improvements of the water distribution system was life cycle cost analysis. In several incidents, a lesser-expensive capital investment option might cost more if operated over the life of the equipment (Leiby and Burke 2011).

Our nature offered way to reduce energy use in the water distribution system that is gravity. The gravitational potential energy could save pumping energy and be substituted for pump power such as hydraulic flocculation. An ideal situation would be treating and delivering water at the water sources where was considerably higher than the demand sites, thus gravitational potential energy could be used for all transportation activities. However, this idea seemed to be far from realistic because it was not financially feasible to reconstruct the entire water system and there were limited water resources at high altitude. A more feasible alternative for the water utility would be to manage the water pressure more effectively. Therefore, there was a need for pump optimization.

2.2.4.1 Pump Optimization

Since most of the water utilities in the developed world had been using Supervisory Control And Data Acquisition (SCADA) systems and operate telemetrically, they could use their historical operational data stored in the database to assist in decision-making and performance improvement (Bunn and Reynolds 2009). The small improvement in term of pump efficiency would result in significant amount of energy saving and consequential drop in carbon emissions to the air.

Initially, a water utility had to make sure that pumps were performing close to the best efficiency point (BEP). The optimization process was very complicated because it involved not only pumps but also several associated pump components such as motor, valves, pipes, etc. The complete understanding of water distribution system characteristics had to be attained before starting the optimization. Activity such as resizing pumps, maintaining consistency, upgrading/rehabilitating motors and others components, etc. were common measures to increase pumps' efficiency. Equipping variable speed or frequency drives to pump motors would increase their efficiency if operating under the optimum output, particularly for low pump capacities. Replacements of old pump motors with more efficient and more appropriate size pumps were advised if it becomes more economical and engineering-sound improvements. The cumulative savings resulted from increasing energy efficiency from a constant use of motors and pumps to a water utility can be significant (Bunn and Reynolds 2009; Leiby and Burke 2011).

2.2.4.2 Pump Scheduling Optimization:

To optimize pump scheduling, first, the initial selection of a pump was important to match operational requirements. Second, the maintenance and refurbishment in a timely manner needed to be well established to continue optimal performance. The last and most importantly process was to dynamically optimize the scheduling of pump operation to improve efficiency. It could be achieved by changing daytime and nighttime water demand patterns to best reflect the daily usage. Moreover, practices of data-mining techniques and real-time dynamic optimizations could considerably increase the energy efficiency to the system (Bunn and Reynolds 2009).

2.2.5 Water Conservation

The U.S. drinking water and wastewater utilities used as much as 56 billion kWh annually—adequate to supply needs of more than 5 million homes for a whole year—that extensive amounts of energy were in demand to treat and deliver water, reported by WaterRF (2011). In the drinking water utilities, the energy would be used for raw water extraction and transportation, treatment, storage, and distribution. Pumping of raw and clean drinking water accounted for a majority of the total energy use. If drinking water utilities could reduce the amount of water being extracted, treated, and distributed, they would save energy magnificently.

Several drinking water utilities and municipal authorities promoted water conservation plans and programs to their industrial and residential sectors in order to decrease water demand (which in turn would reduce the energy costs). Normally, the written water conservation document described the evaluation of existing and future water use. It analyzed infrastructures, operations, and management practices. The conservation plan assessed not only how to reduce the water use, waste, and leakage but also described measures to improve the efficiency of the whole system from treatment, store, and distribution processes (Leiby and Burke 2011).

A holistic approach would help water conservation programs to manage both supply and demand sites more effectively. It also determined alternative water resources for potable and non-potable supplies. Basically, the supply-site focused on managed available water resources, maximized the water utilities operational efficiency, and minimized water loss in the system. Even though implementing the plans would need a substantial amount of financial investment, there were potential revenues from water loss recovery and savings in operating costs. For demand-site approach, the most important problem was a leakage, so implementations of the effective water loss management strategies with conducting water loss audits were recommended by Leiby *et al.* (2011). Results of the water audits would assist utilities to analyze the real loss of water in the system. Then, they could initial programs like proactive leak detection, upgrade water meter accuracy, recordkeeping, repair, and maintenance. The conservation planed for demand-site may decrease revenues of drinking water utilities because of lower in water demand, but a more reflective pricing rate could compensate those expected losses.

Water conservation plans might be varied due to the size of the water utilities and their uniqueness. WaterRF guidelines (2011) for typical water conservation plans included following processes:

- Establish the goals of the water conservation plan
- Conduct a water system audit
- Prepare a demand forecast
- Identify and select potential water conservation measures

2.2.6 Alternative/Renewable Energy Sources and Recovery Energy

Alternative/renewable energy meant energy generated from resources that could naturally regenerate and be used in a sustainable way. Renewable energy projects in the drinking water and wastewater utilities involved equipping with devices or system that could generate energy such as heat and electricity and replacing the use of non-renewable/fossil fuel energy use by renewable energy. It was notable to understand that the renewable energy project principle was to displace the use of energy from fossil fuel with more green and sustainable energy supply. It did not intend to decrease the amount of energy use like energy conservation measures. Therefore, the renewable energy project might have a lengthy return on investments. Most renewable technologies' performances relied on the environmental conditions such as wind, solar radiation, geothermal power, etc. (Leiby and Burke 2011).

The U.S. Environmental Protection Agency (2008) encouraged all drinking water and waste utilities to commit to explore and increase the use of alternative green energy technology rather than the fossil fuel. The benefits of using renewable energy were not only to reduce the environmental impacts but also to save operating costs for water utilities in a long term.

Examples of best practices for alternative/renewable energy sources were:

- Solar Power: Concentrating Solar Power and Photovoltaic Solar Power
- Wind Turbines
- Geothermal
- Lake/ocean Water Cooling
- Micro-Hydro Generation

- Combined Heat and Power Systems

2.2.7 Financial Assistance

Essentially, implementations of the energy efficiency measures would require a considerable amount of capital investment from water utilities. It was crucial for them to know that there were lots of opportunities to apply for financial assistances for projects related reduction in energy consumption and renewable energy use. Many Electric and gas providers provided financial incentives. They, for instance, offered rebates and reduced energy rates for those utilities that installed energy efficient equipment or implemented management practices to improve energy efficiency. In some cases, water utility could take advantages of financing mechanism. It would permit utilities to install energy conservation measures without paying a total amount at once—those installing costs would be paid back out of guaranteed energy savings.

New York State Energy Research and Development Authority Programs and other States funding organizations accommodated a wide range of financial assistances, incentives, and loans. They could come in as shared-cost energy efficiency studies, loan funds to moderate costs of energy efficient equipment, or incentives for renewable energy projects.

For Drinking Water and Clean Water State Revolving Funds (DWSRF and CWSRF), these funds provided low-interest loans for utilities to use for projects such as energy efficiency and water efficiency projects. Utilities might apply funds for installation of water meters, utility energy audits, retrofits or upgrades to pumps or treatment processes, on-site production of clean water, replacement or rehabilitation of pipe, etc.

All in all, drinking water and wastewater utilities were highly encourage to explore available financial assistances to help supporting their energy efficiency projects, and they might have to use a combination of incentive programs and available funding resources to finance the project (Leiby and Burke 2011).

2.2.8 Partnerships

Collaborating with partnerships would help water utilities to pursue many energy efficiency opportunities available. There were two major types of partnerships which were public sector partnerships and fee-supported industry partnerships. These partnerships would circulate management best practices of implementing energy efficiency, share ways to improve energy efficiency, and train water utility operators to enhance their competencies by experts (Leiby and Burke 2011).

First, public sector partnerships usually consisted of federal government, state government, and university. This kind of partnerships provided not only financial support but also information and technical expertise. Public sector partnerships would inform water utilities about existing management best practices and ways/ new technologies to improve system efficiency with no cost. Also, the public sector partnerships would assist utilities to start improving and tracking their energy efficiency measures.

The second type was fee-supported industry partnerships and trade groups that would connect water utilities with a network of industry connections and knowledge for paid subscribers. These trade associates and business networks would allow utilities to expose to other organizations in addition to exchanges of knowledge, best practices, and energy efficiency innovations. Utilities would be benefited for their performance/energy audits and benchmarking by substantial data and information of the industry.

2.3 Development of Energy Benchmarking

There are small numbers of benchmarking studies that considered measuring the energy efficiency. Below were studies that discussed ways to develop benchmarking and to select parameters in order to measure energy efficiency in the water utilities.

2.3.1 Towards the Improvement of the Efficiency in Water Resources and Energy Use in Water Supply Systems:

Souza *et al.* (2010) proposed the methodology to analyze and improve the efficiency in water resources as well as energy use in the water supply systems. The focuses were on water losses and energy management. The studied discussed short, medium, and long term actions for three level of planning including strategic, tactical, and operational. Performance indicators, simulation models, optimization procedures, etc. were identified as decision support tools to address the water loss issue and enhance the energy management in the water supply systems. The performance indicators were rated only as good starting points by authors. They were unable to effectively diagnose the energy use of the whole water system.

2.3.2 Management Evaluation of Water Users Associations Using Benchmarking Techniques:

Córcoles *et al.* (2010) stated that benchmarking was one of many important practices to improve water and energy management. The goals of this study were first to systematically categorize performance and energy indicators. Then, it would apply statistical method to reduce numbers of those indicators. Authors used the Principal Components Analysis (PCA) and the Cluster Analysis

(CA) as the combined application of multivariate techniques to evaluate and group indicators based on their contributions. The study concluded on the most significant indicators that were easy to get and deliver maximum information.

2.3.3 Energy Star:

U.S. EPA (2012) had developed a program called "Energy Star" to promote energy efficiency for both businesses and individuals to help improving not only energy but also financial and environmental performances for participants. The benchmarking scores were statistically calculated and compared with the national average, gathering by U.S. Department of Energy's Energy Information Administration, using a regression analysis to select associated energy parameters. The rating scores from 0 to 100 were proposed representing in percentile basis. Although the mathematical approach in developing the energy benchmarking was useful, the EPA had not had a specific benchmarking for the drinking water utilities.

2.3.4 Measuring Energy Efficiency in Urban Water Systems Using a Mechanistic Approach:

Gay and Sinha (2012) proposed the Thermodynamic Score to evaluate the performance of a utility in comparison with its own potential maximum efficiency. A mechanistic approach could indicate how effectively a water utility performed by compared with its system configuration. The methodology for analysis was developed based on the minimum required energy. For example, factors such as pump efficiency, wire-to-water efficiency, pressure, elevation, friction, head loss, age, etc. were incorporated to find the minimum required energy for each utility. Therefore, this study delivered the intuitive meaning and improved understanding of energy use with in the utility.

2.3.5 Web-Based Benchmarking of Drinking Water Utilities in the United States:

This project was to develop the web-based benchmarking that would allow water utilities to compare performance among peers by Rathor and Sinha (2013). Although there was lots of performance benchmarking available in the industry, they focused on one or few areas of performance. Each benchmarking measured in the similar fashion—which resulted in many repeated indicators—if compared one to the others. Water utilities staff, furthermore, were not be able to answer to some indicators because of differences in the physical characteristics.

Therefore, the authors consulted water utility personals and consultants to evaluate and finalize sets of indicators that well represented the performance of the drinking water utilities. They prioritized indicators that needed to be readily measurable, generic, and comparable. Accordingly, the 57 essential indicators and 32 preferable indicators were chosen to use as the performance benchmarking in the water utilities.

2.3.6 A Meta-Regression Analysis of Benchmarking Studies on Water Utilities Market Structure:

Carvalho *et al. (2012)* conducted benchmarking studies of water utilities market structure. The authors used a statistical method called "meta-regression analysis" to evaluate the impacts of scale and scope economies in the water utilities. The meta-regression was used to investigate the relationships between characteristics (explanatory variables) of samples from public studies with respect to the scale economies and the scope economies (response variables). The study concluded findings based on the statistical significances of each variables, and it used coefficient of the regression model to interpret relationships among variables.

2.3.7 Energy Index Development for Benchmarking Water and Wastewater Utilities:

The Water Research Foundation (WaterRF) (2007), former the American Water Works Association Research Foundation (AwwaRF), took types of energy use, treatment characteristics, services quality, etc. into account to develop energy benchmarking tool for water utilities with an indexed score to make comparisons of energy use among water utilities in the nation. The benchmarking tool was based on the same methodology of US EPA Energy Star for energy efficiency of building using linear regression analysis.

The WaterRF study used a three-parameter regression model that it would judge by highest significance by a *t*-test of a parameter with respect to the Ln [total energy use] parameter and the total flow parameter. To be qualified for the next step, each parameter needed to have *t*-test value higher than 2.0, equivalent to 0.05 *p-value*, to prove to be statistical significant. Six parameters were selected by the industrial experts using the heuristic approach from the pool of 21 independent parameters. Finally, the study conducted the linear regression analysis on those six parameters to fit a model with respect to the total energy use parameter. The WaterRF regression model consisted of six parameters including: 1. Ln[total average flow (MGD)], 2. Ln[average purchased water flow (MGD)], 3. Ln[difference between highest and lowest system elevation (feet)], 4. Ln[source water pumping horsepower (hp)], 5. Ln[length of water mains (feet)], and 6. Ln[total system horsepower (hp)]. The model yielded 0.87 R-Square value.

There were three major concerns about the WaterRF study:

1. The study did not consider relationships between each individual parameters as a whole because it evaluated only three parameters at a time. Therefore, it did not examine the

impact of a parameter that might cause other parameters to be either statistically significant or insignificant if being analyzed all parameters at once.

2. Some of the final parameters were independently chosen based on the nature of the characteristic rather than solely on statistical significance.
3. The study did not take the likelihood of singularity and multicollinearity problems into the consideration. The singularity and multicollinearity problems originated from the collinear data. The regression model should not have neither singularity nor multicollinearity because they would make the regression model unable to accurately analyze the effects of each individual variables.

2.4 Statistical Analyses

2.4.1 Regression

Regression analysis had arguably been the mostly widely used statistical technique for researchers in all field including but not limited to engineering, science, management, economics, etc. (Awe 2013). It had many useful applications to describe, predict, and control relationships between variables (Chatterjee et al. 2000). These applications were often overlapping, and their equations might be valid for some or all of the mentioned purposes. The goal of each regression model would dictate what criteria were needed to be considered in the developing phase, so the selected variables to be in the regression model might be different. As a result, there was no the best set of variables that could flawlessly serve for all purposes.

The purposes of using the regression analysis could be grouped into three main categories (Chatterjee et al. 2000):

2.4.1.1 Description and Model Building:

A regression equation could be used to describe the relationships between variables in the complex interacting system. It could clarify complicated interactions of the given system. In doing so, there were two major methodologies. First method was to have a large numbers of variables in the regression model to account for all possible variations. Second was in the opposite direction which was to have numbers of variables as small as possible for the sake of uncomplicated interpretation and understanding of the regression model. This method chose a smallest set of explanatory variables that could account for considerable parts of variation with respect to the response variable.

2.4.1.2 Estimation and Prediction:

The regression model could be used for purposes of estimation and prediction. The regression equation had the ability to predict the value or estimate the mean response of future observation based on the given information. To build a regression model for these purposes, the main criteria was to have minimum Mean Squared Error (MSE) of prediction while selecting explanatory variables.

2.4.1.3 Control:

The regression model could be treated as a controlling tool. In this case, the regression equation was set as a dependent function that has Y as the dependent variable. The independent/explanatory variables were adjusted to match the particular result of the equation outcome. To use the regression model as a controlling tool, the coefficients of independents variables must be precisely calculated to keep the standard errors of the regression equation small.

2.4.2 Variable Selection Process

In some regression problems, a set of variables were already selected beforehand to be included in the analysis. Usually, the next step was to examine the equation to check the functional specification or assumption about the error terms (Chatterjee et al. 2000). However, there were other regression problems that had not yet determined what variables to be used in the regression equation. Without theories or assumptions assisted in choosing variable, the variable selection procedure was very important step to determine a set of variables for a regression model.

The variable selection procedure could help to select a set of variables from a very large numbers of variables that could be potential predictors. It was the process that analyzes the relationships between predictor variables on how they affected the response variable individually and mutually. There were two ways to select variables in the regression model:

1. All possible regressions (Equation all)
2. Stepwise procedures
   - 2.1. Forward selection
   - 2.2. Backward elimination
   - 2.3. Stepwise regression

2.4.3 All Possible Regressions

Principally, it was a regression type that would evaluate all possible linear regression models of a given pool. The all possible regressions would try to fit all possible combinations of variables that included the intercept of β_0 and all numbers of regression variables. If there were x_i , i = 1,2,3, … , T variables, the all possible regressions would evaluate the total of 2^T potential models (Golberg and Cho 2004). Since the all possible regressions would calculate all possible subsets of the pool of variables, it would select the best model based on given criteria. The criteria could be as following:

1. R-Square – quantity of the variation in the response from the least square fit
2. RMSE – Root Mean Square Error
3. Cp – Mallow's C_p criterion
4. AICc – Corrected Akaike's Information Criterion
5. BIC – Bayesian Information Criterion

In comparison with the Stepwise regression, the all possible regression had many advantages over the Stepwise procedures (Golberg and Cho 2004). First, the three methodologies in the stepwise procedures could not guarantee any type of optimality in the model. Second, three methodologies of the Stepwise procedures did not essentially have the same set of regressors in their final model. Third, the Stepwise procedures sometimes selected a set of regressors that were not "uniquely superior" from a pool of independent variables. Lastly, all of these three methodologies would provide only one final model; therefore, the researcher was forced to accept the model unconditionally even though that model might or might not be the "best" regression model.

Regarding the variables selection process, Golberg and Cho (2004) stated that "The aim of selection is always to maximize the ability to find out all of the 'relevant' information that is hidden in the data." Thus, all possible regression resulted to be a better option to find the "best" regression model.

2.4.4 Bayesian Information Criterion (BIC):

BIC calculates a model fit, and it was useful to compare between models (Golberg and Cho 2004), as defined in Equation 1. The smaller number of BIC suggested a better fit. BIC was calculated based on model fitness and complexity (number of variables). While the RSquare value tended to increase with adding more variables to the model, BIC did not essentially change in that similar pattern. It would, however, change with the combination of regressors to indicate the value of fitness in the model. According to SAS Institute Inc. (2013), BIC could be termed as:

$$-2loglikelihood + k\ln(n) \qquad \textbf{EQUATION [1]}$$

where

- -2loglikelinood was computed by:

  n * (ln (2 * pi ( ) *SSE/n) + 1)
- k was the number of regressors
- n was the number of observations

Although both BIC and AICc (corrected Akaike's Information Criterion) were helpful measures to compare fitness of models, BIC tended to select fitted models that had less parameters than AICc (NCSS 2014). A set of selected explanatory variables based on smallest BIC were believed to achieve both prediction capability (as many significant parameters as needed) and simplicity (as minimum significant parameters as possible). Therefore, this study chose to use BIC as the model selection criterion.

2.5 Collinear Data

Collinear data could cause serious distortions if being analyzed by a standard procedure (Chatterjee et al. 2000). If there were one or more small eigenvalues existing in the correlation matrix, it was likely to have a collinearity problem. Essentially, there were two approaches to solve a collinearity. First was to identify variables that cause collinearity, and sequential action was to delete them to have a reduced dataset of noncollinear variables. The second method was to use a tool called "ridge regression." However, this method was not applicable to data set with a large numbers of variables. Practically, the first method of deleting correlated variables was almost always selected to compute variables selection with collinear data.

2.5.1 Singularity

In general, the simple linear regression model was formulated as in the Equation 2 (SAS 2013). If the regression model had *p* parameters and *n* observations, the X became *n* x *p* matrix.

$$Y = \beta X + \varepsilon \qquad \textbf{EQUATION [2]}$$

The regression coefficient β could be found as shown in the Equation 3 below.

$$\beta = [(X^T X)^{-1}][X^T Y] \qquad \textbf{EQUATION [3]}$$

The coefficient, β, could be computed only if $(X^T X)$ was nonsingular and invertible (Golberg and Cho 2004; SAS 2013). However, in the case of singular matrices, the invert matrix of $(X^T X)$ was incomputable because there were linear dependencies between parameters. There would be at least one parameter that it was a roughly linear combination of a group of remaining parameters.

2.5.2 Multicollinearity

The problems occurred when one or more independent variables (explanatory parameters) were highly correlated with other independent variables. When independent variables were adequately redundant, the impact of singularity and severe multicollinearity caused inability to accurately distinguish effects of each variable.

The Variance Inflation Factors (VIF) and the correlation of parameter estimates could be used to identify multicollinearity in the dataset.

2.5.3 Variance Inflation Factors (VIF)

VIF could indicate whether or not a specific variable had multicollinearity with respect to other explanatory variables in the group and the response variable, as shown in Equation 4. VIF was calculated from each of the explanatory variable in the model as a function of all other explanatory variables. The VIF for the X_j term could be defined as (SAS 2013):

$$VIF_j = \frac{1}{1-R_j^2}, \qquad j = 1, \ldots, p \qquad \textbf{EQUATION [4]}$$

where

- p was the number of explanatory parameters in the regression model
- R_j^2 was the coefficient of multiple determination, i.e. RSqure, for the regression of x_j as a function of the other explanatory parameters

If the X_j had a strong linear relationship with other explanatory variables in the model, it would make R_j^2 value close to 1 and VIF_j value large (Chatterjee et al. 2000). Golberg and Cho (2004) wrote that if VIF value was greater than 10, it would suggest a possibility of having the multicollinearity problem in the model. Consequently, multicollinearity might cause problems in the estimating process.

2.5.4 Correlation of Parameter Estimates

The correlation of parameter estimates matrix is calculated to evaluate whether or not the collinearity is present in the model (SAS 2013). The typical linear regression formula is defined as:

$$Y = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p + \varepsilon \qquad \textbf{EQUATION [5]}$$

where

- $\beta_0, \beta_1, \ldots, \beta_p$ were the coefficients
- $X_1, X_2, \ldots, X_p$ were explanatory variables
- ε was an error

In individual row of the data table, there were a value for response variable and values for the p explanatory variables. The explanatory variables were considered unchanged in each observation, while a response variable was considered as a function of a random variable. With fixed values of explanatory variables for any set of response variables, the coefficient could be estimated. The estimated coefficients could be different depended on the different set of response variables. The correlation of parameter estimates, then, computed the theoretical correlation of the estimated coefficients.

The correlation of parameter estimates calculated merely on an estimated of the interception and values of the explanatory variables (SAS 2013). More importantly, the values of response variables had no effect on a correlation between a pair of two explanatory variables estimates. Values of the correlation of parameter estimates were in a range of -1 and 1. The correlation value at 1 indicated a direct relationship between a pair of explanatory variables in a perfect increasing linear relationship, while the correlation value at -1 implied a direct relationship between a pair of explanatory variables in a perfect decreasing linear relationship (Golberg and Cho 2004). If the correlation value was at 0, it meant that the relationship between a pair of explanatory variables was uncorrelated with little or no linear relationship.

2.5.5 Solving Multicollinearity

Multicollinearity problem could be solved. First, similar purposed variables were grouped together. Multicollinearity diagnostic measures was run to identify variables that most likely to have multicollinearity problem. The most widely used methodology to eliminate the collinear of data was to delete a variable that had high VIF score (Chatterjee et al. 2000). If the VIF value was higher than 10.0, it was likely that the variable would have multicollinearity (Golberg and Cho 2004). After detected collinearities, a group of variables that had VIF value over 10 would be analyzed separately to explore relationships among them. The correlation of parameter estimates investigatesd pairwise comparisons among the variables in the group. The high number would indicate that a pair of variables is likely to have collinear relationship between them (SAS 2013). With results from both VIF and the correlation of parameter estimates, a group of variables with a collinear dataset was identified. The following step was to delete one variable from this group out one at a time based on the least statistical significances (highest Prob>|t| value). The rest of the available variables would check the VIF with respect to the response variable to find multicollinearity. The iteration would be repeated until none of variables in the pool have VIF value greater than 10, thus it achieved the status of noncollinear dataset.

2.5.6 Collinearity Elimination Framework

Based on the discussed methodologies, the proposed framework is recommended to eliminate collinear problems in the dataset as shown in the Figure 1. The framework starts with processing dataset and then checks the singularity and multicollinearity among variables. It will repeat the cycle of eliminating correlated variables until singularity and/or multicollinearity do not exist.

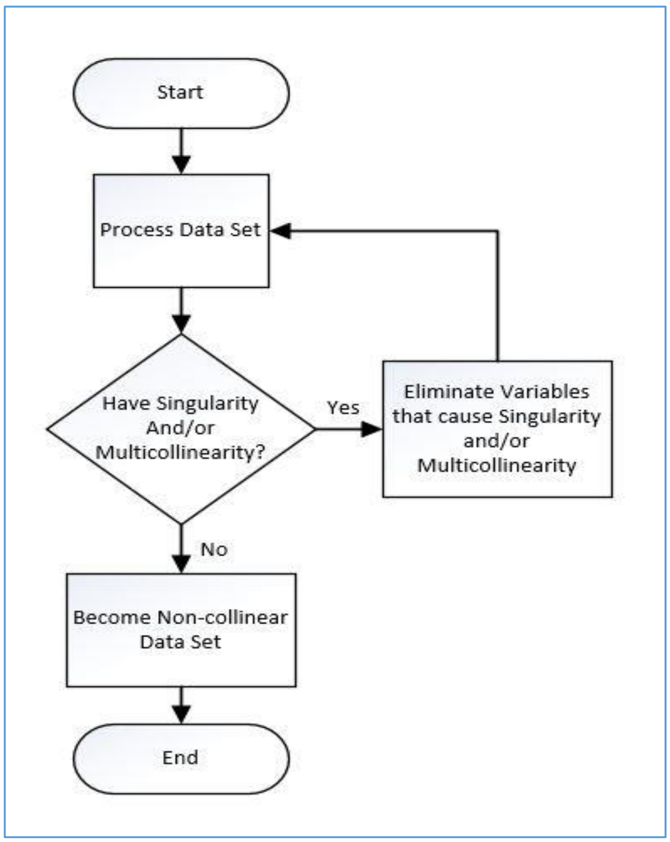


FIGURE 1: PROPOSED FRAMEWORK TO ELIMINATE SINGULARITY AND MULTICOLLINEARITY

CHAPTER 3. METHODOLOGY

3.1 Data Collection

The study used the WaterRF (2007) survey da5a that was published with the *Energy Index Development for Benchmarking Water and Wastewater Utilities* report. The WaterRF created this survey to gather operating characteristic and energy use of the drinking water utilities. It was developed based on templates of U.S. EPA ENERGY STAR benchmarking system for commercial buildings, American Municipal Sewage Association (now the National Association of Clean Water Agencies), EPA Community Water System, and Iowa surveys. The WaterRF sent out the water utility survey instrument to 1,723 water utilities across the geographic distribution of the U.S. It received the data back from 389 water utilities.

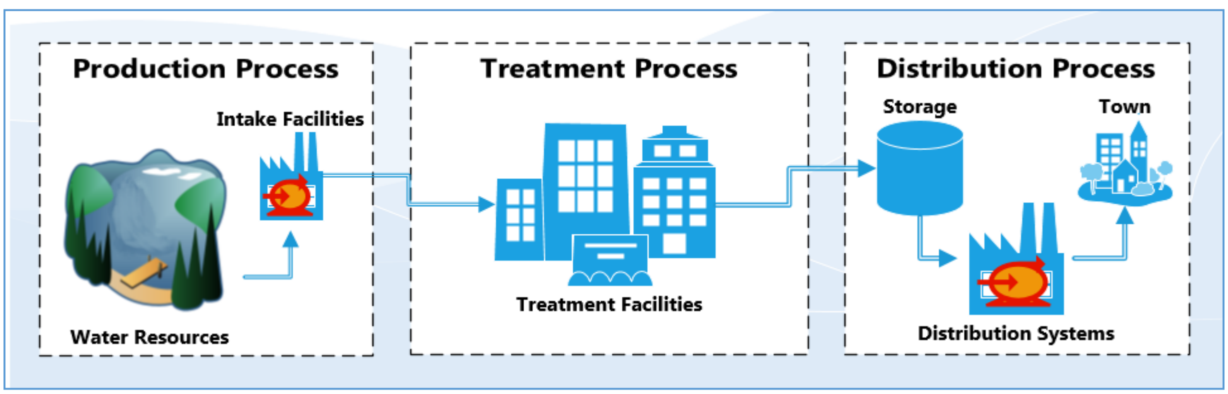


FIGURE 2: A SCHEMATIC DIAGRAM OF A TYPICAL DRINKING WATER UTILITY

In a typical drinking water utility, there would be three main processes according the WaterRF (2007). They were production process, treatment process, and distribution process as shown in the Figure 2 above. The parameters in this study consisted of 104 parameters measuring throughout a water utility including water general parameters, raw water parameters, water treatment objectives, water treatment processes and residual handling parameters, water distribution parameters, and water energy use parameters. All parameters were attached in the Appendix A. The study had samples from 389 water utilities across the U.S. The geographical distribution was displayed in Figure 3 below.

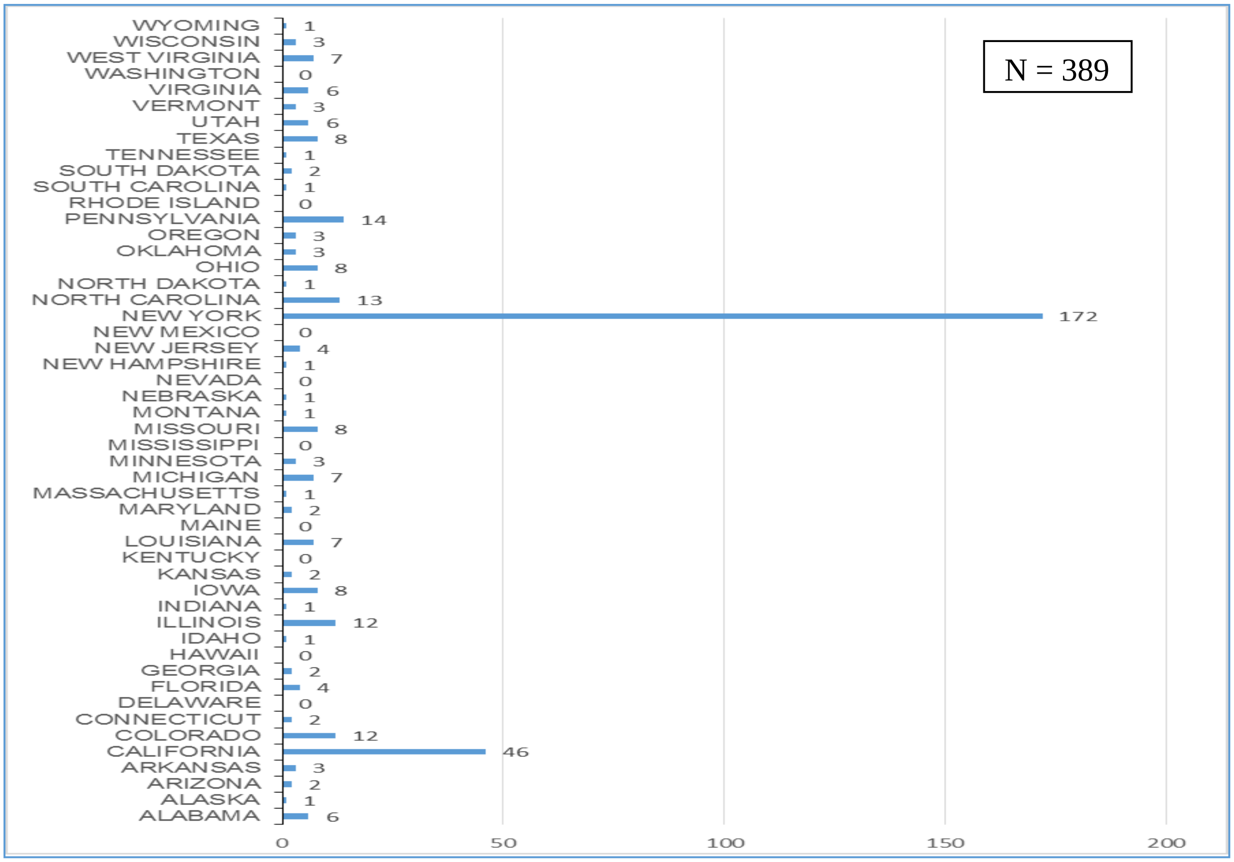


FIGURE 3: WATER UTILITY SAMPLES GEOGRAPHICAL DISTRIBUTION

Statistically speaking, terms of a "variable" and a "parameter" were used interchangeably in this study. Essentially, a variable was any value, quantity, or characteristic of an observation. While in the benchmarking term, a variable could be referred as a "parameter" that contained value of a specific system characteristic. An observation was a survey result having information of parameters from a water utility.

3.2 Observations

The process of this study started from the available 389 survey samples of water utilities. The first decision-making point was to set research criteria. The research criteria mainly considered missing value in each observation. First of all, the observation had to have the total energy use greater than 0 kBtu. Since this parameter was the only response parameter in this study, the regression could not analyze energy related relationships from explanatory parameters without it. 188 observations had either 0 kBtu or missing value. Also, it happened that 46 observations from New York utilities had missing values in 13 quantitative parameters that measured horsepower, turbidities, well depth, and elevations. Therefore, these 46 observations were excluded from the study as well.

The rest of the observations, then, had not been removed or modified to prevent bias and incorrect relationships that may occur in the regression models. Therefore, the total numbers of available observations were at 155 utilities.

3.3 Parameters

There were 104 parameters in each water utility observation. Out of these 104 parameters, 58 parameters were qualitative variables while 46 were quantitative variables. Most of the qualitative parameters were nominal. Nominal parameters meant that values belonged to groups and the order did not matter. Those were binary questions. Also, some of qualitative parameters were ordinal. Ordinal values belonged to groups, and the order mattered. For example, the number of ground water source was recorded by count, but the magnitude of the water source was not given.

Therefore, the decision was made to exclude those 58 qualitative parameters out of the total 104 parameters of this study. The relationships between the total energy use and those qualitative parameters were not meaningful to make any comparisons in this study. As a result, only 46 quantitative parameters (continuous variables) were included in the parameter selection process. In the group of 46 quantitative parameters, parameters could be divided into categories. First was a category of 16 direct energy use parameters to be used as response parameters, and the second group was indirect energy use parameters that consisted of 30 explanatory parameters.

3.3.1 Response Parameter

The direct energy use parameters measured the amount of energy use in terms of electricity, natural gas, fuel oil, and propane as well as their associated costs. The list of these 16 direct energy use parameters, parameter #1-16, was shown in Table 2.

TABLE 2: DIRECT ENERGY USE PARAMETERS

#	Analysis Columns	N	Mean	Max	Min	Std Dev	Sum
1	Production Electricity Use (KWH)	155	4,292,597.91	150,000,000.00	0.00	14,028,200.81	665,352,676.00
2	Production Electricity Peak (KW)	155	253,540.02	34,000,000.00	0.00	2,731,403.48	39,298,702.69
3	Poduction Electricity Cost ($)	155	253,386.85	4,771,000.00	0.00	592,257.23	39,274,961.00
4	Treatment Electricity Use (KWH)	155	2,452,087.66	83,300,956.00	0.00	9,058,937.43	380,073,587.00
5	Treatment Electricity Peak (KW)	155	13,248.03	466,440.00	0.00	52,085.43	2,053,444.56
6	Treatment Electricity Cost ($)	155	163,643.72	6,335,118.00	0.00	610,519.62	25,364,777.00
7	Distribution Electricity Use (KWH)	155	5,834,798.11	248,255,578.00	0.00	24,745,195.01	904,393,706.54
8	Distribution Electricity Peak (KW)	155	121,836.17	15,000,000.00	0.00	1,209,921.79	18,884,606.82
9	Distribution Electricity Cost ($)	155	392,221.72	16,930,986.00	0.00	1,601,087.20	60,794,367.00
10	Total Electricity Use (KWH)	155	14,923,925.88	248,255,578.00	0.00	33,342,635.88	2,313,208,511.00
11	Total Electricity Peak (KW)	155	407,386.92	50,000,000.00	0.00	4,034,417.21	63,144,973.22
12	Total Electricity Cost ($)	155	950,439.91	16,930,986.00	0.00	1,973,110.16	147,318,186.00
13	Natural Gas Use (THERMS)	155	301,499.86	21,035,803.00	0.00	2,381,358.72	46,732,478.90
14	Natural Gas Cost ($)	155	47,943.94	1,044,089.00	0.00	153,504.26	7,431,310.00
15	Fuel Oil and Propane Amount (kBtu)	155	21,736,692.85	400,427,573.00	4,230.00	86,980,259.09	456,470,549.93
16	Purcahsed Energy Cost ($)	155	3,742.31	169,391.00	0.00	20,223.26	580,058.00
17	Total Energy Use (kBtu)*	155	199,474,134.59	3,920,218,166.00	666,000.00	532,510,736.90	30,918,490,861.43
18	Ln[Total Energy Use (kBtu)]**	155	17.75	22.09	13.41	1.59	2,750.53

All of these 16 direct energy use parameters were considered as response parameters. They would be used to find relationships with other 30 indirect energy use parameters, which were the parameter #1-30 in the Table 3.

The singularity was found in the group of the total electricity use parameter in Equation 6. The total electricity use parameter was the combination of production electricity use parameter, treatment electricity use parameter, and distribution electricity use parameter. These parameters became redundancies if they were included in the models (Golberg and Cho 2004). Therefore, only the total electricity use was selected from this group.

Total Electricity Use (kWh) = Production Electricity Use (kWh) + Treatment Electricity Use (kWh) + Distribution Electricity Use (kWh) **EQUATION [6]**

There was a need of a signal energy use parameter to represent the whole group of 16 direct energy use parameters. First, the single parameter, the total energy use parameter (parameter #17), was created to best capture effects of the entire group based on the annual average use of energy as defined in Equation 7. This study used the source energy conversion factors according to the WaterRF (2007) to convert electricity (parameter #1,4,7,10 in Equation 6), natural gas (parameter #13), fuel oil and propane use (parameter #15) to be in a single unit of British thermal unit (Btu) for the total energy use parameter.

Total Energy Use (kBtu) = [Total Electricity Use (kW) X 11.1 (kBtu/kWh)] + [Natural Gas Use (Therm) X 102.4 (kBtu/Therm)] + [Fuel Oil (Gallon) X 141 (kBtu/Gallon)] + [Propane (Gallon) X 91 (kBtu/Gallon)] **EQUATION [7]**

These conversion factors were calculated based on the amount of energy in Btu to product a kWh of electricity. It would take US national average of 11,100 Btu to generate a kWh of electricity (DOE 2004). Fuel oil and propane were converted from a unit of sale volumes in gallon to kBtu. In case of the natural gas, the conversion factor already took 2.4% transmission losses into an account. The study used the natural logarithm to transform the total energy use parameter

(parameter #17) in Figure 4 to be Ln [total energy use] parameter (parameter #18), so it would have a normal distribution instead of skewed distribution as shown in Figure 5.

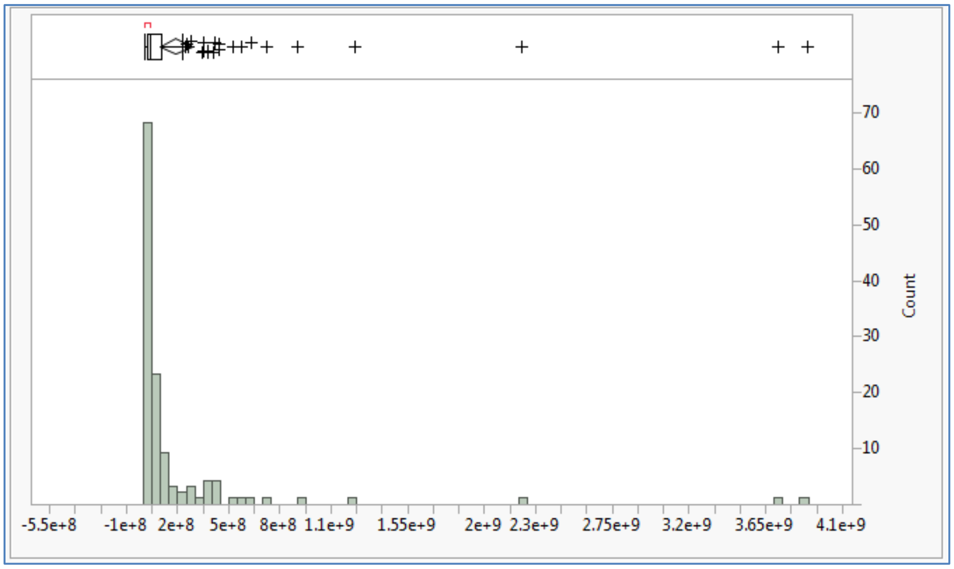


FIGURE 4: TOTAL ENERGY USE PARAMETER

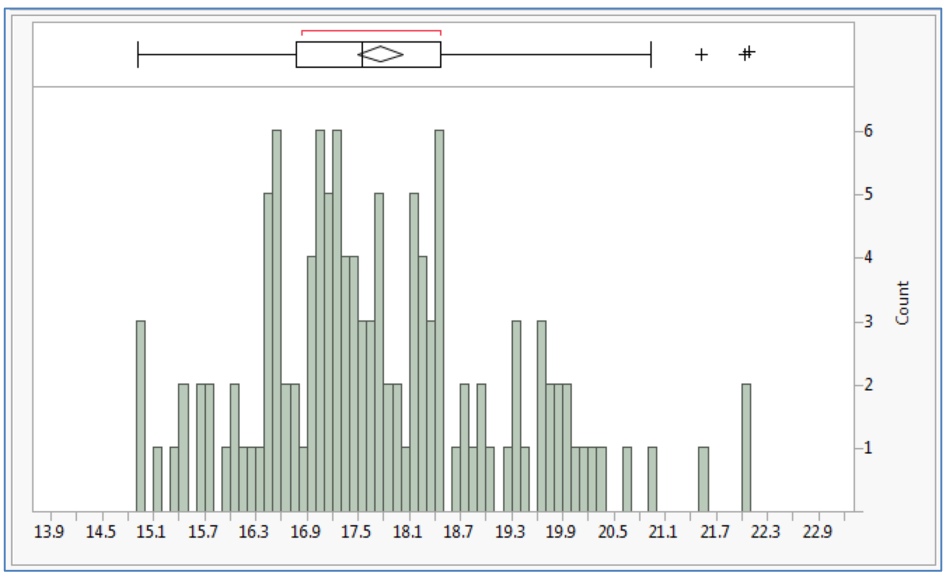


FIGURE 5: LN [TOTAL ENERGY USE] PARAMETER

A set of energy cost parameters (parameter #3,6,9,12,14,16) and a set of peak energy use parameters (parameter #2,5,8,11) were highly correlated with a set of energy parameter use parameters (parameter #1,4,7,10). As the test discovered multicollinearity among them, they were statistically redundant with the Ln [total energy use] parameter. The Ln [total energy use parameter was also compared with the original 16 parameters to find the relationships among them to see if this parameter can be the best candidate for the group of 16 parameters. The founding of singularity and multicollinearity indicated that these 17 parameters are collinear dataset, when having the Ln [total energy use] parameter as a response variable and other 16 parameters as independent variables. Results suggested that having only one response parameter (parameter #18) was recommended to avoid problem of this collinear dataset.

All in all, the study selected the Ln [total energy use] parameter (parameter#18) to represent as the only response variable of this study.

3.3.2 Explanatory Parameters

In this group, there were 30 indirect energy use parameters (parameter #1-30 in table 3) that could be used to explain the relationship with the response parameter.

TABLE 3: INDIRECT ENERGY USE PARAMETERS

#	Title	N	Mean	Max	Min	Std Dev	Sum
1	Average Ground Water Flow (MGD)	155	4.15	57.85	0.00	9.05	643.90
2	Design Ground Water Flow (MGD)	155	7.32	90.03	0.00	15.58	1,135.25
3	Maximum Ground Water Flow (MGD)	155	8.96	173.00	0.00	21.28	1,389.07
4	Average Surface Water Flow (MGD)	155	16.94	568.00	0.00	57.37	2,625.47
5	Design Surface Water Flow (MGD)	155	25.96	728.00	0.00	79.50	4,023.54
6	Maximum Surface Water Flow (MGD)	155	36.87	1,457.53	0.00	138.03	5,714.81
7	Average Purchased Water Flow (MGD)	155	3.53	205.00	0.00	18.29	546.70
8	Average Well Depth (FT)	155	287.46	2,500.00	0.00	446.53	44,557.03
9	Source Water Pumping Horse Power (HP)	155	1,929.84	14,000.00	0.00	3,235.68	299,124.50
10	Average Ground Turbidity (NTU)	155	0.41	10.00	0.00	1.40	63.64
11	Peak Ground Turbidity (NTU)	155	3.45	200.00	0.00	20.90	535.52
12	Average Surface Turbidity (NTU)	155	6.59	210.40	0.00	19.57	1,021.58
13	Peak Surface Turbidity (NTU)	155	122.48	5,524.00	0.00	496.38	18,985.02
14	Total Average Daily Residuals (LB/DAY)	155	21,477.84	2,000,000.00	0.00	163,286.12	3,329,065.14
15	Population of Service Area (People)	155	162,320.57	2,896,000.00	0.00	394,839.56	25,159,689.00
16	Size of Service Area (SQM)	155	99.92	1,200.00	0.00	190.95	15,487.72
17	Length of Water Mains (Miles)	155	534.47	4,240.00	0.00	843.65	82,842.40
18	High Elevation (FT)	155	1,174.32	9,430.00	-35.00	1,464.13	182,019.38
19	Low Elevation (FT)	155	817.61	9,300.00	-42.00	1,338.83	126,729.28
20	Distribution Pumping Horse Power (HP)	155	2,850.57	44,230.00	0.00	6,162.31	441,839.00
21	Total Storage Volume (MG)	155	559.47	80,375.00	0.00	6,455.48	86,717.75
22	Average Distribution Pressure (PSI)	155	71.28	491.00	0.00	40.95	11,048.00
23	Unaccounted for Treated Water (%)	155	10.19	92.00	0.00	11.45	1,579.58
24	Total Building Area (SQFT)	155	77,772.79	4,000,000.00	0.00	454,536.40	12,054,782.25
25	Engine Driven Pump Horse Power (HP)	155	371.17	12,417.00	0.00	1,325.43	57,531.00
26	Total Average Flow (MGD)	155	24.62	568.00	0.00	59.93	3,816.07
27	Average raw turbidity (NTU)	155	6.53	210.40	0.00	19.50	1,011.73
28	Peak raw turbidity (NTU)	155	182.28	8,464.20	0.00	761.42	28,253.20
29	Difference between highest and lowest system elevation (FT)	155	356.71	1,800.00	-10.00	380.95	55,290.10
30	Total System Horse Power (HP)	155	5,151.58	57,530.00	0.00	8,430.90	798,494.50

The interpretation of multiple linear regression could be made if the assumption was true that the explanatory parameters were not strongly correlated (Chatterjee et al. 2000). If the singularity and/or multicollinearity existed in the dataset, the estimated effects of each parameter in the linear regression were unreliable. For that reason, the interpretation of this study might not be valid because there were strong linear relationships between these 30 indirect energy use parameters.

The study used the statistical approach that was discussed earlier in the collinear data section of chapter #2 to eliminate both singularity and multicollinearity problems in this dataset. The Figure 6 showed three-step process to address the collinear dataset. The first step was to eliminate the singularity; there were 10 parameters with identified singularity out of a pool of 30 explanatory parameters. The second and third steps were to exclude parameters that had multicollinearity out of the dataset. Two parameters of the second step and three parameters of the third step were classified with multicollinearity. The total of 15 explanatory parameters were available for the parameter selection process.

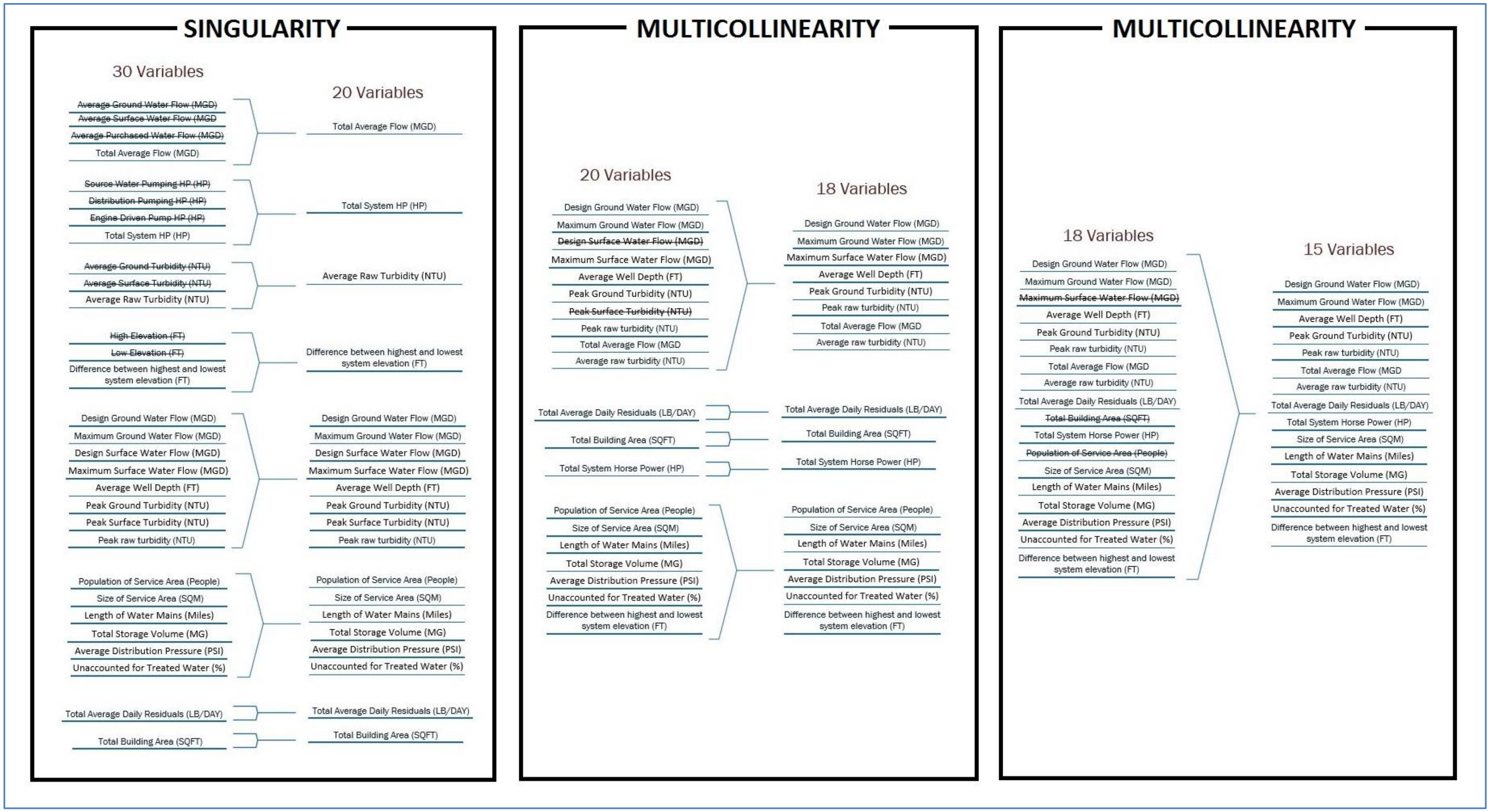


FIGURE 6: ELIMINATION OF COLLINEAR PARAMETERS PROCESS

3.3.2.1 Singularity

The following groups of parameters had singularity problems among themselves. They were groups of total average flow parameter (parameter #1,4,7,26 in Equation 8), total system horsepower parameter (parameter #9,20,25,30 in Equation 9), average raw turbidity parameter (parameter #10,12,27 in Equation 10), and difference between highest and lowest system elevation parameters (parameter #18,19,29 in Equation 11).

Total Average Flow (MGD) = Average Ground Water Flow (MGD) + Average Surface Water Flow (MGD) + Average Purchased Water Flow (MGD) **EQUATION [8]**

Total System Horsepower (HP) = Source Water Pumping Horsepower (HP) + Distribution Pumping Horsepower (HP) + Engine Driven Pump Horsepower (HP) **EQUATION [9]**

Average Raw Turbidity (NTU) = [Average Ground Turbidity (NTU) + Average Surface Turbidity (NTU)] / 2 **EQUATION [10]**

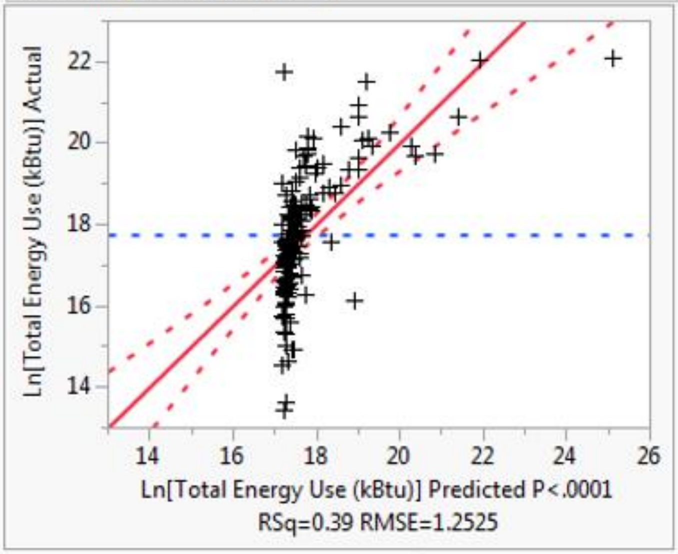
Difference between Highest and Lowest System Elevation (FT) = High Elevation (FT) - Low Elevation (FT) **EQUATION [11]**

The study used the JMP program from SAS to identify singularity in the dataset. The group of parameters that shared the same unit were analyzed to check the singularity. In Figure 7, four parameters of the Equation 8 were checked as explanatory parameters with respect to the response parameter. As the result, the study found singularity detials that the total averge flow parameter had direct relationship with the sum of average groud water flow, average surface water flow, and avearge purchase water flow.

Singularity Details

Total Average Flow (MGD) = Average Ground Water Flow (MGD) + Average Surface Water Flow (MGD) + Average Purchased Water Flow (MGD)

Actual by Predicted Plot



Summary of Fit

RSquare	0.390813
RSquare Adj	0.37871
Root Mean Square Error	1.252464
Mean of Response	17.74536
Observations (or Sum Wgts)	155

Parameter Estimates

Term		Estimate	Std Error	t Ratio	Prob>|t|
Intercept		17.19644	0.116931	147.06	<.0001*
Total Average Flow (MGD)	Biased	0.0144539	0.005522	2.62	0.0098*
Average Ground Water Flow (MGD)	Biased	0.0484596	0.012526	3.87	0.0002*
Average Surface Water Flow (MGD)	Biased	-0.000487	0.005735	-0.08	0.9325
Average Purchased Water Flow (MGD)	Zeroed	0	0	.	.

FIGURE 7: SINGULARITY DIAGNOSIS

Since a parameter could sufficiently represent the effect of the whole group, other parameters in the group were judiciously excluded from the study to eliminate singularity in the model. As a result, ten parameters were removed from the study as shown in Figure 8. The number of available parameters in this category became 20 parameters.

Singularity #1	Average Ground Water Flow (MGD)	Removed
	Average Surface Water Flow (MGD)	Removed
	Average Purchased Water Flow (MGD)	Removed
	Total Average Flow (MGD)	

Singularity #2	Source Water Pumping Horse Power (HP)	Removed
	Distribution Pumping Horse Power (HP)	Removed
	Engine Driven Pump Horse Power (HP)	Removed
	Total System Horse Power (HP)	

Singularity #3	Average Ground Turbidity (NTU)	Removed
	Average Surface Turbidity (NTU)	Removed
	Average Raw Turbidity (NTU)	

Singularity #4	High Elevation (FT)	Removed
	Low Elevation (FT)	Removed
	Difference between highest and lowest system elevation (FT)	

FIGURE 8: ELIMINATIONS OF SINGULARITY

3.3.2.2 Multicollinearity

The next step was to exclude parameters with multicollinearity problem from a pool of 20 explanatory parameters. Having multicollinearity in the model, the regression would inaccurately select parameters into a model because it was unable to analyze effects of each individual parameters.

Raw Water Parameters	Design Ground Water Flow (MGD)	
	Maximum Ground Water Flow (MGD)	
	Design Surface Water Flow (MGD)	Removed
	Maximum Surface Water Flow (MGD)	
	Average Well Depth (FT)	
	Peak Ground Turbidity (NTU)	
	Peak Surface Turbidity (NTU)	Removed
	Peak raw turbidity (NTU)	
	Total Average Flow (MGD)	
	Average raw turbidity (NTU)	
Water Residual Handling Parameter	Total Average Daily Residuals (LB/DAY)	
Water Distribution Parameters	Population of Service Area (People)	
	Size of Service Area (SQM)	
	Length of Water Mains (Miles)	
	Total Storage Volume (MG)	
	Average Distribution Pressure (PSI)	
	Unaccounted for Treated Water (%)	
	Difference between highest and lowest system elevation (FT)	
Water General Parameter	Total Building Area (SQFT)	
	Total System Horse Power (HP)	

FIGURE 9: MULTICOLLINEARITY DIAGNOSIS 1ST ITERATION

The parameters were grouped together based on similarity of measuring characteristics. In Figure 9, the first iteration was based on the four different groups of WaterRF classification (2007). The second iteration was all remaining parameters after the first iteration as shown in Figure 10.

All Available Parameters	Design Ground Water Flow (MGD)	
	Maximum Ground Water Flow (MGD)	
	Maximum Surface Water Flow (MGD)	Removed
	Average Well Depth (FT)	
	Peak Ground Turbidity (NTU)	
	Total Average Daily Residuals (LB/DAY)	
	Population of Service Area (People)	Removed
	Size of Service Area (SQM)	
	Length of Water Mains (Miles)	
	Total Storage Volume (MG)	
	Average Distribution Pressure (PSI)	
	Unaccounted for Treated Water (%)	
	Total Building Area (SQFT)	Removed
	Total Average Flow (MGD)	
	Average raw turbidity (NTU)	
	Peak raw turbidity (NTU)	
	Difference between highest and lowest system elevation (FT)	
	Total System Horse Power (HP)	

FIGURE 10: MULTICOLLINEARITY DIAGNOSIS 2ND ITERATION

Analyzing the multicollinearity used Variance Inflation Factors (VIF) to discover parameters with the problems. If the VIF value was higher than 10.0, it was suggested that the parameter had the multicollinearity (Golberg and Cho 2004). In Figure 11, the discovering process highlighted four parameters that had VIF values higher than 10.0.

#	Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
1	Population of Service Area (People)	-9.4e-7	1.02e-6	-0.92	0.361	21.16
2	Length of Water Mains (Miles)	8.63e-4	3.4e-4	2.54	0.012	10.71
3	Total Building Area (SQFT)	1.93e-8	6.28e-7	0.03	0.975	10.57
4	Total Average Flow (MGD)	6.44e-3	4.63e-3	1.39	0.167	10.02
5	Peak Raw Turbidity (NTU)	-1.1e-3	3.31e-4	-3.37	0.001	8.27
6	Average raw turbidity (NTU)	4.31e-2	1.28e-2	3.37	0.001	8.07
7	Total System Horse Power (HP)	3.69e-5	1.79e-5	2.06	0.041	2.97
8	Size of Service Area (SQM)	-3.3e-4	7.57e-4	-0.44	0.662	2.71
9	Design Ground Water Flow (MGD)	1.81e-2	9.23e-3	1.97	0.051	2.69
10	Maximum Ground Water Flow (MGD)	-1.4e-3	6.27e-3	-0.23	0.820	2.31
11	Total Average Daily Residuals (LB/DAY)	1.63e-6	7.66e-7	2.12	0.035	2.03
12	Total Storage Volume (MG)	-3.6e-6	1.89e-5	-0.19	0.848	1.93
13	Difference between highest and lowest system elevatio...	3.51e-4	2.52e-4	1.39	0.166	1.20
14	Unaccounted for Treated Water (%)	2.23e-2	8.28e-3	2.69	0.008	1.17
15	Average Well Depth (FT)	8.16e-5	2.12e-4	0.39	0.700	1.16
16	Average Distribution Pressure (PSI)	-3.4e-3	2.21e-3	-1.53	0.128	1.07
17	Peak Ground Turbidity (NTU)	-5.2e-3	4.25e-3	-1.22	0.226	1.03
-	Intercept	1.68e+1	2.33e-1	71.87	0.000	•

FIGURE 11: VIF CALCULATION

The next step was to see the relationships between those four parameters through the Correlation of Parameter Estimates as shown in Figure 11. The values were in the range between -1 to 1. The positive value recommended that a pair of parameters were highly correlated with the positive slope, while the values negative suggested that a pair of parameters were highly correlated with the negative slope. The zero value meant that a pair of parameter had no relationship between them. More information was discussed in the section 2.4.4. In Figure 12, the high values of correlated pairs of parameters both positive and negative were highlighted in red. The population of service area parameter was highly correlated with the total average daily residuals, length of water mains, and total building area parameters. The total building area parameter was excluded from the study because it had the highest Prob>|t| (smallest t Ratio) values among parameters with multicollinearity in Figure 11. The parameter with the multicollinearity would be exclude out one at a time until the dataset became non-collinear.

#	Row	Population of Service Area (People)	Length of Water Mains (Miles)	Total Building Area (SQFT)	Total Average Flow (MGD)
-	Intercept	0.079	-0.124	-0.038	-0.065
1	Design Ground Water Flow (MGD)	0.095	-0.198	0.067	-0.097
2	Maximum Ground Water Flow (MGD)	0.049	0.026	-0.019	-0.012
3	Average Well Depth (FT)	-0.006	0.091	-0.042	0.055
4	Peak Ground Turbidity (NTU)	-0.052	0.056	0.035	-0.009
5	Total Average Daily Residuals (LB/DAY)	-0.427	0.271	0.472	-0.186
6	Population of Service Area (People)	1.000	-0.671	-0.621	-0.148
7	Size of Service Area (SQM)	0.175	-0.556	0.101	-0.111
8	Length of Water Mains (Miles)	-0.671	1.000	0.321	-0.041
9	Total Storage Volume (MG)	-0.298	-0.006	0.598	-0.425
10	Average Distribution Pressure (PSI)	-0.041	0.004	0.020	0.072
11	Unaccounted for Treated Water (%)	0.022	-0.017	-0.088	0.126
12	Total Building Area (SQFT)	-0.621	0.321	1.000	-0.556
13	Total Average Flow (MGD)	-0.148	-0.041	-0.556	1.000
14	Average raw turbidity (NTU)	0.123	-0.079	0.006	-0.104
15	Peak Raw Turbidity (NTU)	-0.113	0.076	-0.011	0.100
16	Difference between highest and lowest system elevation (FT)	-0.007	0.089	0.121	-0.135
17	Total System Horse Power (HP)	-0.265	-0.159	0.417	-0.294

FIGURE 12: MULTICOLLINEARITY ANALYSIS

After two iteration of multicollinearity diagnosis, five parameters were subsequently removed because of having multicollinearity problems. In fact, each of those five parameters had VIF value greater than 10. These parameters were 1.) Design surface water flow, 2.) Peak surface turbidity, 3.) Maximum surface water flow, 4.) Population of service area, and 5.) Total building area. There were only 15 remaining explanatory parameters in the pool.

3.3.3 Parameters Selection Framework:

The parameters selection framework, as shown in Figure 13, was developed based on the principle of statistics. It would assist in the decision-making process to select a set of statistically significant parameters that was highly associated with the total energy use parameter from a pool of collinear data.

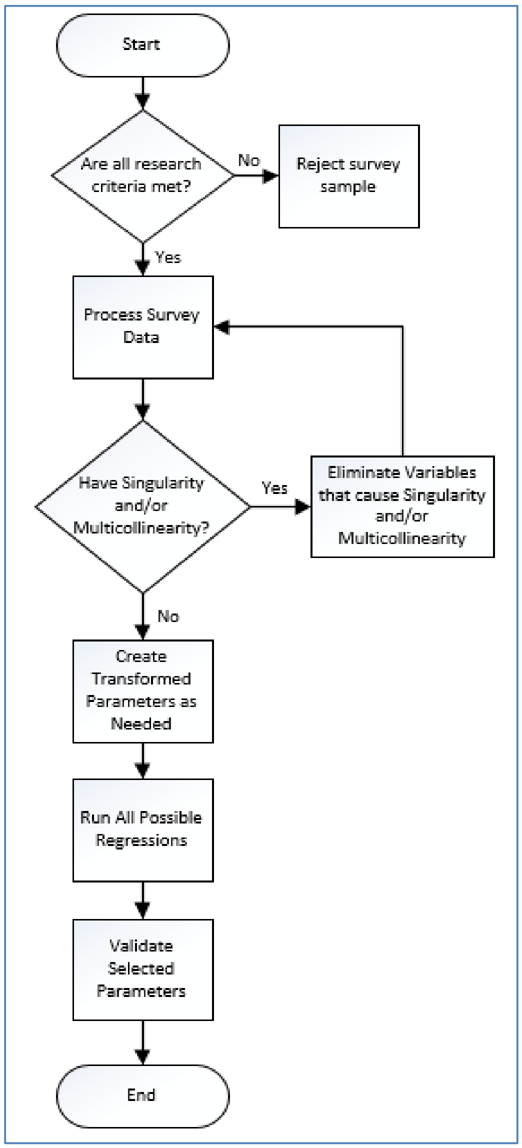


FIGURE 13: PARAMETERS SELECTION FRAMEWORK

This framework would scrutinize and recommend appropriate actions for issues such as the qualitative parameters, missing values in observations, singularity, and multicollinearity within the dataset. The following step was to analyze pairwise relationships between each explanatory parameter and the response parameter. If a relationship of a pair was not a straight-line relationship, the transformed parameter of the original explanatory parameter was created as an additional parameter. For instance, the transformation could be in forms of a log scale or polynomial to any degrees that would yield the highest R-Square value. Below are the criteria:

1. Analyzed the pairwise comparisons between the Ln [total energy use] parameter and each of the 15 explanatory parameters

2. Created a transformed parameters if other forms of the 15 explanatory parameters had better R-Square values

3. All original 15 explanatory parameters remained for the analysis

	Model	Number	RSquare
1	Ln[Total System Horse Power (HP)]	1	0.4618
2	Total System Horse Power (HP)	1	0.3717
3	(Total System Horse Power (HP))*(Total System Horse Power (HP))	1	0.1101
4	(Total System Horse Power (HP))*(Total System Horse Power (HP))*(Total System Horse Power (HP)	1	0.0647

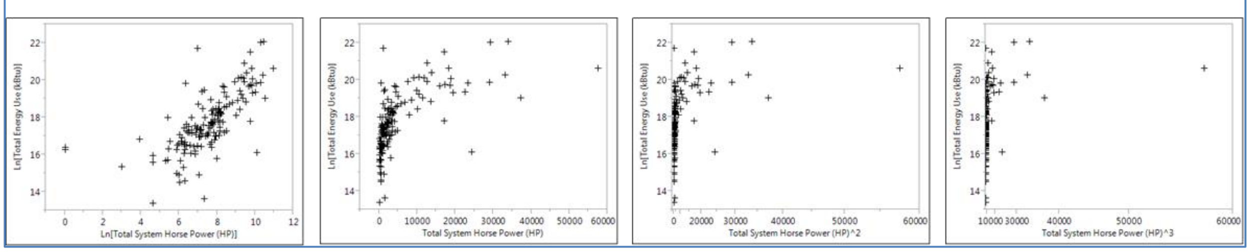


FIGURE 14: SELECTION OF THE TRANSFORMED PARAMETERS

In Figure 14, the total system horse power parameter was compared with the Ln [total system horse power] parameter, (total system horse power parameter)^2, and (total system horse power parameter)[3] to find the best R-Square values. The Ln [total system horse power] parameter had the best R-Square value, so it was kept for the next analysis. If the original form of parameter had the best R-Square value, no additional transformed parameter would be needed.

As a result, the total number of explanatory parameters became 24 parameters that would be used for the all possible regressions analysis. The 15 parameters were in their original forms, while 9 parameters were transformed using a natural logarithm. The list of 9 transformed parameters included:

1. Design Ground Water Flow (MGD)
2. Maximum Ground Water Flow (MGD)
3. Total Average Daily Residuals (LB/DAY)
4. Size of Service Area (SQM)
5. Length of Water Mains (Miles)
6. Total Storage Volume (MG)
7. Total Average Flow (MGD)
8. Peak raw turbidity (NTU)
9. Total System Horse Power (HP)

The set of these 24 parameters were noncollinear, so they were ready to be selected through all possible regressions based on the lowest BIC value.

CHAPTER 4. RESULT AND DISCUSSION

4.1 The Selection of Models

Results of all possible regressions ranked effects of each individual parameter by R-Square value. In Table 4, there were 15 explanatory parameters in their original forms and additional 9 transformed parameters. The Ln [total average flow] parameter had the highest R-Square value at 0.552 following by the Ln [total system horsepower] parameter at 0.462 and the length of water main parameter at 0.440 respectively.

TABLE 4: INDIVIDUAL PARAMETER EFFECT WITH RESPECT TO THE TOTAL ENERGY USE

#	Model	Number	RSquare	RMSE	AICc	BIC
1	Ln[Total Average Flow (MGD)]	1	0.552	1.065	460.58	469.53
2	Ln[Total System Horse Power (HP)]	1	0.462	1.167	488.80	497.75
3	Length of Water Mains (Miles)	1	0.440	1.190	494.85	503.81
4	Total System Horse Power (HP)	1	0.372	1.261	512.63	521.59
5	Total Average Flow (MGD)	1	0.314	1.318	526.15	535.10
6	Ln[Total Storage Volume (MG)]	1	0.276	1.354	534.48	543.43
7	Ln[Length of Water Mains (Miles)]	1	0.276	1.354	534.56	543.51
8	Ln[Size of Service Area (SQM)]	1	0.210	1.414	547.82	556.77
9	Size of Service Area (SQM)	1	0.177	1.443	554.23	563.18
10	Design Ground Water Flow (MGD)	1	0.113	1.499	565.76	574.71
11	Ln[Total Average Daily Residuals (LB/DAY)]	1	0.112	1.499	565.90	574.85
12	Total Average Daily Residuals (LB/DAY)	1	0.063	1.540	574.21	583.16
13	Ln[Design Ground Water Flow (MGD)]	1	0.063	1.540	574.22	583.17
14	Maximum Ground Water Flow (MGD)	1	0.056	1.546	575.34	584.29
15	Ln[Peak raw turbidity (NTU)]	1	0.034	1.564	578.84	587.79
16	Ln[Maximum Ground Water Flow (MGD)]	1	0.033	1.564	579.00	587.95
17	Difference between highest and lowest system elevation (FT)	1	0.025	1.571	580.30	589.25
18	Total Storage Volume (MG)	1	0.012	1.581	582.28	591.23
19	Peak Ground Turbidity (NTU)	1	0.008	1.585	582.96	591.92
20	Unaccounted for Treated Water (%)	1	0.005	1.587	583.46	592.41
21	Average raw turbidity (NTU)	1	0.002	1.590	583.92	592.87
22	Peak Raw Turbidity (NTU)	1	0.000	1.591	584.12	593.07
23	Average Distribution Pressure (PSI)	1	0.000	1.591	584.13	593.08
24	Average Well Depth (FT)	1	0.000	1.591	584.14	593.09

If there were 24 independent parameters, selecting all possible subsets to fit a model ranging from 1 parameter at a time to 24 parameters at a time would result to be 16,777,216 possible models. All possible regressions calculated the RSquare, RMSE (Root Mean Square Error), AICc, and BIC for all 16,777,216 possible models. The total of 231 models were plotted in the Figure 15. Those were models that had up to 10 lowest RMSE for each incremental number of parameters from 1-24 terms.

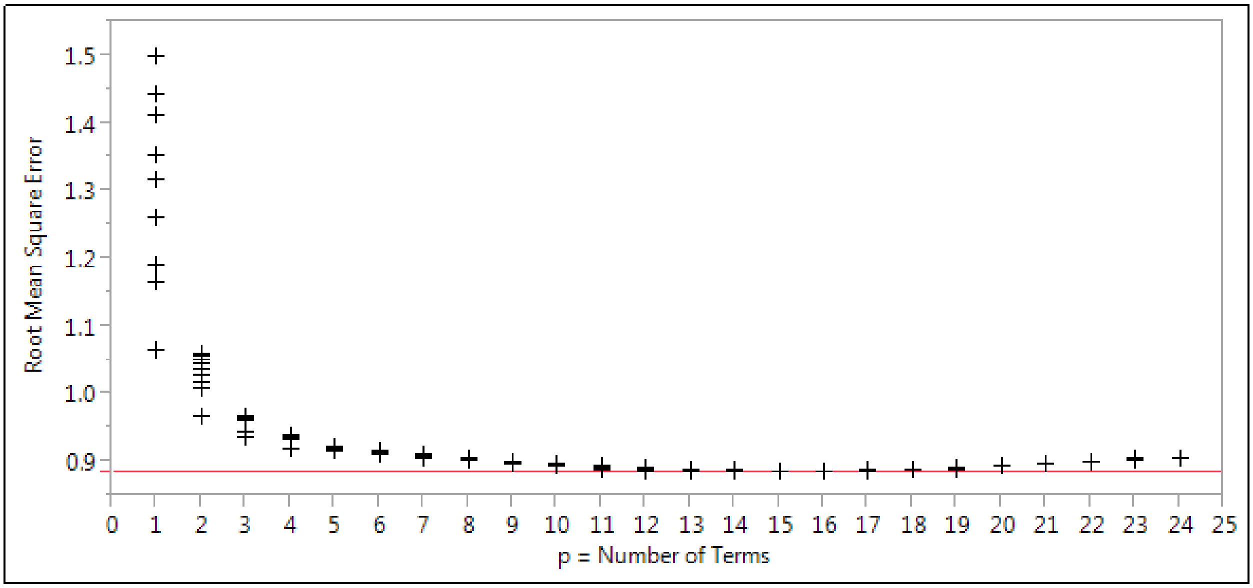


FIGURE 15: SUBSETS OF ALL POSSIBLE REGRESSIONS

RMSE was the square root of the Mean Square for Error that measured the standard deviation of the random error (SAS 2013). The small the number of RSME, the better fit of the model would be. However, RMSE was typically decreased with adding more terms to a model. The interest of simplicity was usually one of the major factors for choosing the regression model along with goodness of fit according to Golberg *et al.* (2004). The BIC was calculated based on both model fit and complexity of the model, please see Equation 1. Therefore, the BIC was suggested to use as indexes in this study to compare fitness among models (SAS 2013).

The three models in Table 5 had the smallest BIC value among all possible subsets. The first model had 4 parameters with 436.66 BIC. The second and third models had three and five parameters respectively with slightly larger BIC values than the first model at 437.74 and 439.11 respectively.

TABLE 5: SELECTED MODELS OF ALL POSSIBLE REGRESSION

Model	Parameter	Number of Term	Rsquare	RMSE	AICc	BIC
1	1. Length of Water Mains (Miles) 2. Unaccounted for Treated Water (%) 3. Ln[Total Average Flow (MGD)] 4. Ln[Total System Horse Power (HP)]	4	0.672	0.921	419.01	436.66
2	1. Length of Water Mains (Miles) 2. Ln[Total Average Flow (MGD)] 3. Ln[Total System Horse Power (HP)]	3	0.659	0.936	422.96	437.74
3	1. Length of Water Mains (Miles) 2. Average Distribution Pressure (PSI) 3. Unaccounted for Treated Water (%) 4. Ln[Total Average Flow (MGD)] 5. Ln[Total System Horse Power (HP)]	5	0.677	0.916	418.62	439.11

4.2 Discussion of the Final Model

The model #1 in the Table 5 was selected to be the final model of this study. In Figure 16, the value of Prob > F in the analysis of variance was small enough to indicate a very convincing significance that these four parameters were statistically significant in the regression model. Statically speaking, the set of these four parameters was highly associated with the Ln [total energy use] parameter and had no singularity and multicollinearity. The adjusted R-Square value of the model was at 0.663. These four parameters were 1. length of water main (miles), 2. unaccounted for treated water (%), 3. Ln [total average flow (MGD)], and 4. Ln [total system horsepower (HP)]. The detail of all possible regressions result was presented in Figure 16. The Figure 17 showed relationships between four parameters and the Ln [total energy use] parameter.

Summary of Fit

RSquare	0.672
RSquare Adj	0.663
Root Mean Square Error	0.921
Mean of Response	17.76
Observations (or Sum Wgts)	154

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	4	258.48231	64.6206	76.2624
Error	149	126.25443	0.8473	Prob > F
C. Total	153	384.73674		<.0001*

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|	VIF
Intercept	14.141364	0.388756	36.38	<.0001*	.
Length of Water Mains (Miles)	0.0003798	0.000123	3.08	0.0025*	1.96
Unaccounted for Treated Water (%)	0.0162299	0.006605	2.46	0.0151*	1.04
Ln[Total Average Flow (MGD)]	0.5005557	0.081464	6.14	<.0001*	2.26
Ln[Total System Horse Power (HP)]	0.2908413	0.058203	5.00	<.0001*	1.69

AICc	BIC
419.01	436.66

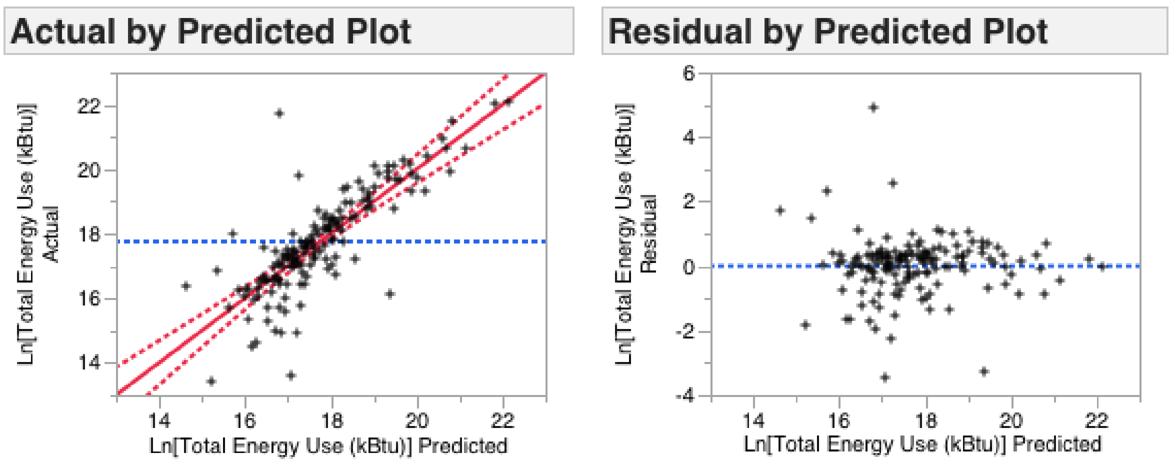


FIGURE 16: ALL POSSIBLE REGRESSIONS RESULT

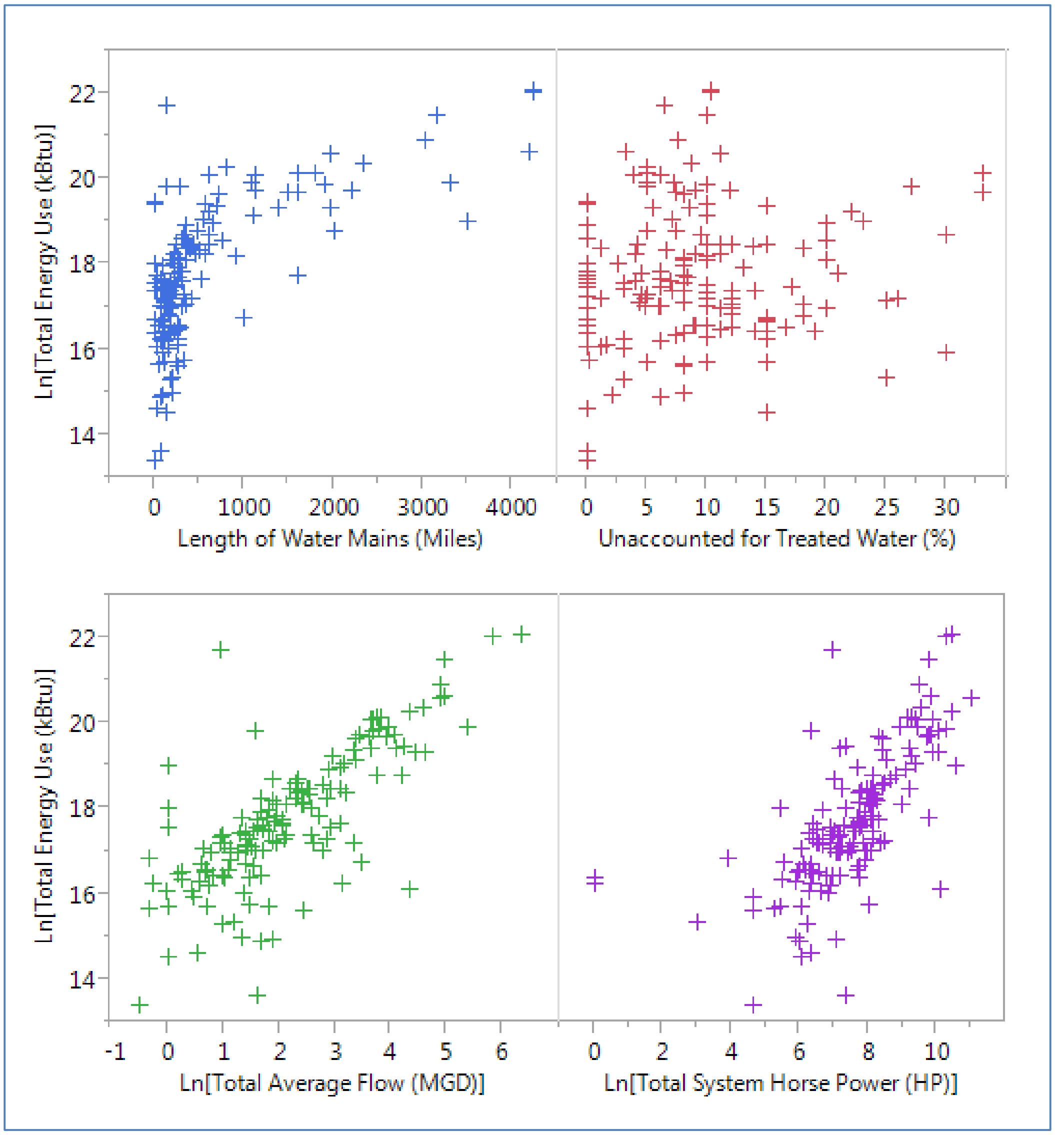


FIGURE 17: ACTUAL TOTAL ENERGY USE VS SELECTED PARAMETERS

The length of water mains (miles) parameter was statistically significant because the longer the pipe, the more horsepower required to distribute water. The unaccounted for treated water (%) parameter, i.e. water loss through leakage, was directly equal to the loss of treated water and horsepower in the system. Also, the energy was wasted because of the water treatment process and the use of pumps in the system as the indirect consequences of the water loss. The Ln [total average flow (MGD)] parameter was directly proportional to the amount of energy required to treat and transport water. This meant that the higher the total average flow, the higher the energy demanded to treat water. The reason that Ln [total system power (hp)] parameter was considered to be highly related with total energy use because the system horsepower was use to maneuver water throughout the system. Furthermore, factors like high fiction loss, static pressure, leakage, etc. would result in larger pump motor horsepower required.

Figure 18 showed the areas that each of the four parameters could be used to measure the energy use in the water utility. In fact, this water utility model was production-oriented model. It was used in this study in order to correspond with the structure of the WaterRF survey data.

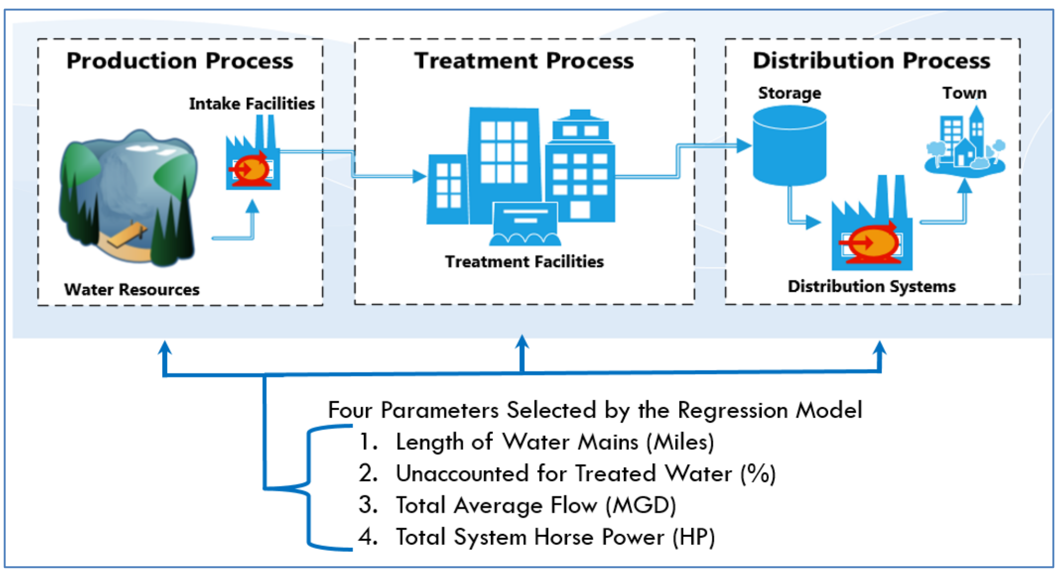


FIGURE 18: RELATIONSHIPS BETWEEN FOUR ENERGY PARAMETERS AND A WATER UTILITY

All in all, the all possible regressions gave the flexibility to select models with compromise between model fit and simplicity. In the future, the methodology would provide water utilities options to select the model based on cost-effective analysis. For example, some parameters are more economical and easier to collect the data than other parameters. Therefore, it may be more practical to choose some model over the others with a compromise on slightly lower accuracy of prediction capability.

4.3 Improve Energy Efficiency in the Water Utilities

While consumers mostly dictate the amounts of total flow and water main length, areas of total system horsepower (pumps) and water loss can be improved significantly. Followings are some examples on how to improve energy efficiency for these two parameters. Leiby and Burke (2011) recommended to improve the total system horsepower by installing new pumps that are better fitting sized and more efficient. Also, the practices such as real-time dynamic optimization technologies and data-mining techniques could be implemented to increase the energy efficiency (Bunn and Reynolds 2009) along with Energy and Water Quality Management System (EWQMS) (Jentgen et al. 2007). Increasing in the energy efficiency even by small percentages can lead to substantial savings for consistently used motors and pumps over a period of time.

The unaccounted for treated water parameter measures is the water loss in the system. Implementing leak assessment methodology can help to recognize leakage in the system (Lansey et al.). Leak detection technologies such as infrared thermography, random/regular sounding survey, acoustic, etc. can help to locate leaks. Reducing leakage would reduce both loss of treated water and amount of energy used to treat water. It also improves the public health protection and reliability of the water supply systems (Fanner et al. 2007).

4.4 Challenges and Lessons Learned

The author realized through conducting this study that there were many possibilities to improve the energy benchmarking in drinking water utilities.

1. The qualitative parameters should be avoided in the survey. The survey had 58 out of 104 parameters as qualitative parameters, i.e. binary variables with yes and no questions. These qualitative parameters could not provide any good indications on how the energy was being used in the system. For example, if a utility stated that it used a slow sand filtration process, there was no amount of energy provided to make comparisons with other utilities in the nation.
2. The ordinal number type parameters (values belong to groups, and the order matters) in the survey needed to be normalized. Those parameters were given numbers that were simply labels. They had no real quantitative value. For instance, the total number of pumps parameter was incomparable without knowing the sizes of those pumps. The pump size could be an enormous one at 5,000 hp or a very tiny one at 10 hp, but each individual pump was counted as one pump. It did not take magnitudes into the consideration.

   To normalize these ordinal parameters, the survey should create new parameters to improve comparing capability. For example, the new parameters should be created in a series of amounts according to flow rate range, pressure range, or horsepower range instead of the total number of pumps parameter.
3. Incorporating the condition assessment parameters into the benchmarking was needed to compare the current state of the system. The designed pump horsepower might not reflect the real operational routine if the pump only was run constantly at its 70 percent efficiency.

4. To improve accuracy of the energy benchmarking, the survey samples ought to be grouped together utilities with similar characteristics such as the quality of raw water, system topography, or specifically environmental and financial regulation. Then, the energy benchmarking should be conducted among utilities within the same class.

   It was not meaningful to compare the utilities in different places just based on a simple parameter such as their energy use per unit cost. The study of Leiby and Burke (2011) showed that an average retail price for electricity in New York was about 40 to 60 percent higher than the rest of the US. The New York water and wastewater section, therefore, had to spend approximately 35 percent more than the national average per unit basis even though its utilities had roughly 10 percent more efficient than in the other states.

5. The survey data was not nationally distributed. Although the surveys were sent out to all 50 states, there were 9 states with zero response. The total of 26 states had two or fewer responses. It was desired to have richer data to develop a genuinely national energy benchmarking.

6. All missing value should be reported as missing/blank value not zero. It was possible that some recorded zero value in observations might be missing/unreported values. Those zero values found in the dataset might not be truly zero but placeholders for missing values. Therefore, those zero values should not be treated as missing values and vice versa because their effects were significantly different.

7. The dataset had relatively small numbers of useful observations. Some of the parameters had extremely small variation, but others were highly different. Thus, the decision to remove parameters out of the model because of the multicollinearity had to be made on

very sensitive information. The results would possibly change if adding just a few more observations. Therefore, there was a need for larger and good quality dataset.

4.5 A Schematic Diagram of the Improving Cycle of Energy Benchmarking

The cycle in Figure 19 is recommended by the author to improve the energy benchmarking. The figure is a schematic diagram of the improving cycle of energy benchmarking in drinking water utilities. This study was in the study to improve the current practice phase that would help to improve energy benchmarking. There still is a need to have better defined parameters to capture characteristics of the water utilities in a more effective way as in the improvement phase. Therefore, researchers could have the improved energy benchmarking to collect new data to upload in the national online database. The national online database was discussed in the future work section. Consequently, this cycle would improve the performance of the future energy benchmarking in both reliability and accuracy.

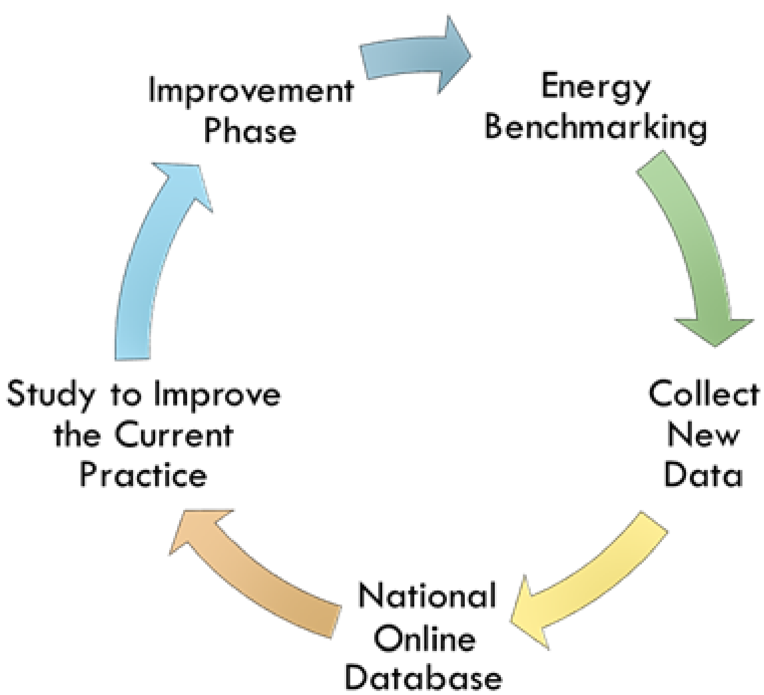


FIGURE 19: IMPROVING CYCLE OF ENERGY BENCHMARKING IN DRINKING WATER UTILITIES

CHAPTER 5. CONCLUSION

It was important to know how individual plan configuration, load, and operational factors could be linked and affect to the energy use of water utilities. In doing so, energy benchmarking could be a very useful tool to measure how energy is being used in the systems. It was also a crucial step to improve the energy performance of the drinking water utilities. Having energy benchmarking, the utilities could use those parameters to improve their energy efficiency.

The goal of this study was to use a quantitative approach to select energy benchmarking parameters for the drinking water utility. It would use a mathematically objective method rather than heuristic assumptions and/or subjective approach from the industrial experts.

The study used the national survey data of the drinking water utilities collected by the WaterRF. Although the WaterRF survey was collinear dataset, those parameters with singularity and/or multicollinearity were statistically examined and excluded from the dataset. The study applied the variables selection method, called "all possible regressions," to select a subset of parameters from available independent/explanatory parameters in noncollinear dataset. Significant parameters that were statistically selected based on their statistical significance. As a result, the all possible regressions provided list of models that each had different subsets of explanatory parameters. In each model, individual parameters were considered as highly associated with the total energy use parameter. The model was selected based on the lowest BIC value. The regression model was believed to have a good predictive capability to estimate the total energy use of a water utility.

It was suggested by the author that following steps of the improving cycle should be taken to arrive the desired energy benchmarking in drinking water utilities: energy benchmarking; collect new data; national online database; study to improve the current practice; and improvement phase.

CHAPTER 6. FUTURE WORK

The future work is to develop a good survey instrument with better-defined parameters. It was clear that the data collecting protocol ought to be improved. It is needed to concentrate on energy related parameters and avoid qualitative parameters. All parameters should be normalized and incorporate current condition assessment. To get a better perception of energy efficiency in water utilities, the energy benchmarking should benchmark among utilities that have similar system characteristics to avoid high benchmarking outcome variation, if comparing against utilities with totally different system operational features.

The integration of existing technologies will improve the reliability and accuracy of data. Implementation of sensors is recommended not only to eliminate human errors but also to improve the data recording frequency. Also, the internet can improve communication paths to get data from water utilities faster instead of a current practice that is heavily relied on the postal mail service. The ultimate goal is to have real-time data of all participated water utilities available in online database. The last step would be to develop algorithms to do real-time analysis and update benchmarking results online accessible for user interface through a standard website or an application of a mobile device.

The author would like to discuss two practical features of the energy benchmarking, WATER*i*D and the benchmarking rating score. They can be improve substantially with better defined energy benchmarking and richer dataset.

6.1 WATER*i*D – An Online Database

WATER*i*D is the water infrastructure database that shares useful information online through web interface. The online benchmarking has been developed for water utilities on this database, but there is no specially energy benchmarking yet. The process of getting the data started from survey files are sent to a water utility electronically. The files are in standard forms asking to fill out values of parameters. The water utility will be asked to save those files in the File Transfer Protocol (FTP). Next, the Extract, Transform, and Load (ETL) program is used to deliver the data from the files located in the FTP and then display them on the WATER*i*D. The data extraction process in Figure 20 is programed to be automated. The example of the benchmarking result is displayed in the Figure 21. The benchmarking data could be made publically accessible. The online database and web interface could improve the collecting data process because it makes the process easier and quicker to communicate between researchers, water utilities, and consumers.

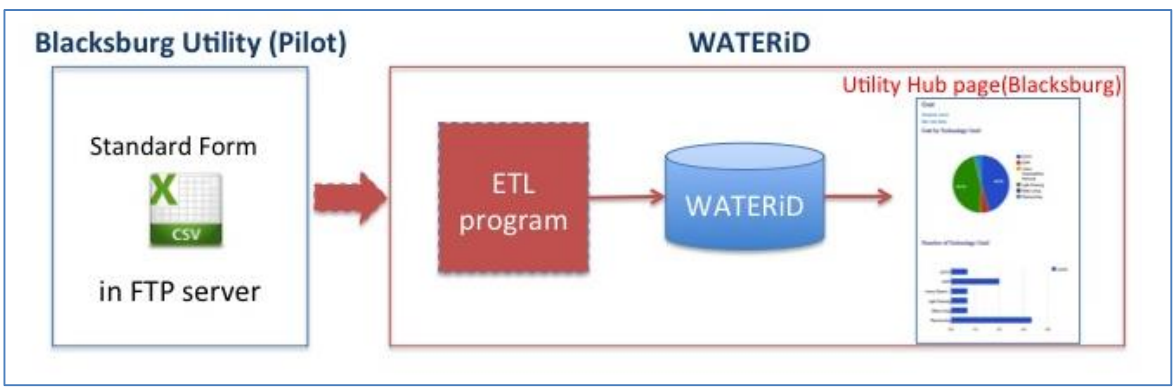


FIGURE 20: THE DATA EXTRACTION PROCESS OF WATERID

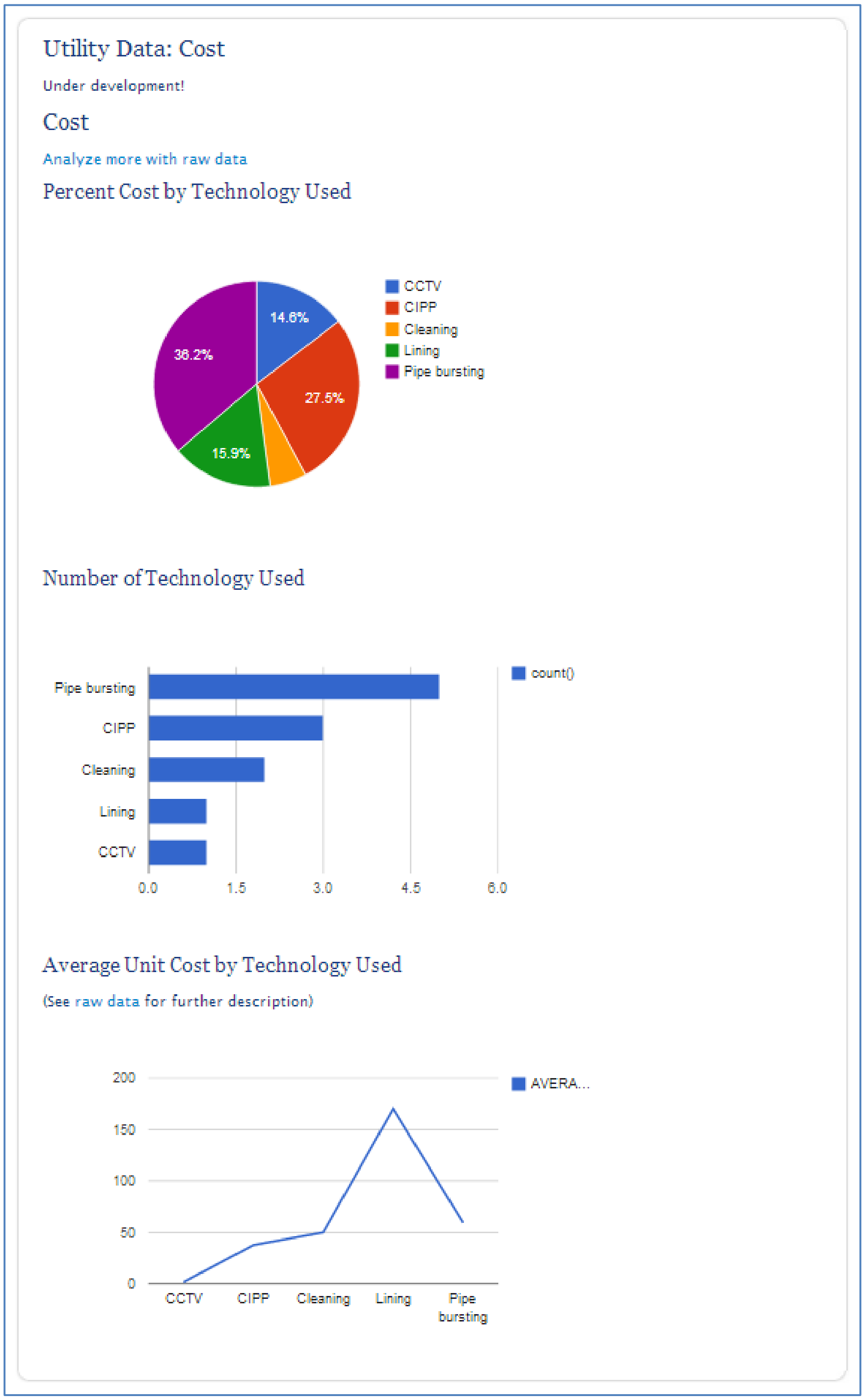


FIGURE 21: WATERID BENCHMARKING EXAMPLE

6.2 Benchmarking Rating Score

The benchmarking rating score is developed to help water utilities to compare themselves with peers in the industry. After having a better defined survey instrument, a new dataset will be collected from water utilities with similar characteristics. The dataset will use the parameter selection framework and all possible regressions to select a set of significant parameters with respect to the total energy use. The final regression model is chosen, so that the regression equation can be formulated. The regression model will be able to predict the energy use of a water utility. The energy use ratio is defined in Equation 12. A water utility will be asked the actual energy use along with values of significant parameters of the final regression model. The values of significant parameters will be used to calculate the predicted energy use in the regression equation.

$$Energy\ Use\ Ratio = \frac{Actual\ Energy\ Use}{Predicted\ Energy\ Use} \qquad \textbf{EQUATION [12]}$$

In Figure 22, the Ln [energy ratio] values were graphed to see the distribution. The ratio of 1 means that the actual energy use is equal to the predicted energy use. If the ratio is lesser than 1, it indicates that a water utility consumes energy less than the predicted value. If the ratio is greater than 1, it implies that a utility use energy more than the predicted value. It is crucial to know that the following examples are shown solely for the conceptual purposes. The actual results may be different from these examples.

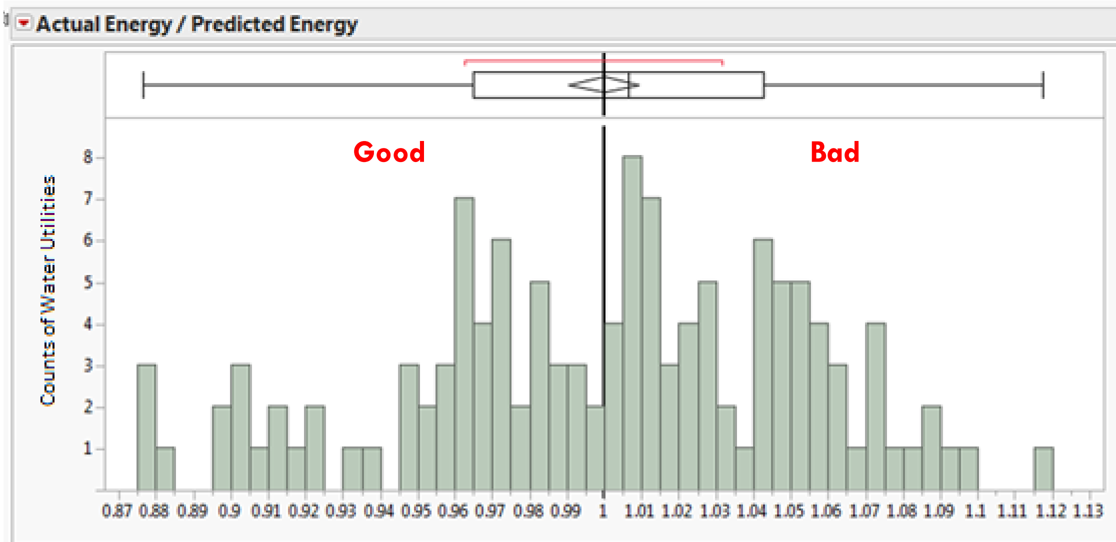


FIGURE 22: DISTRIBUTION OF LN [ENERGY USE RATIO]

To compare the energy use ratio of a water utility with other utilities in the industry, the cumulative probability graph of Ln [energy use ratio] is created from energy use ratio of all utilities, as shown in Figure 23. For example, if a water utility has an energy use ratio at 0. 95, the energy performance score of that water utility would be ranked at the 85 percentile (1.0 - 0.15 = 0.85) among peers in the water industry.

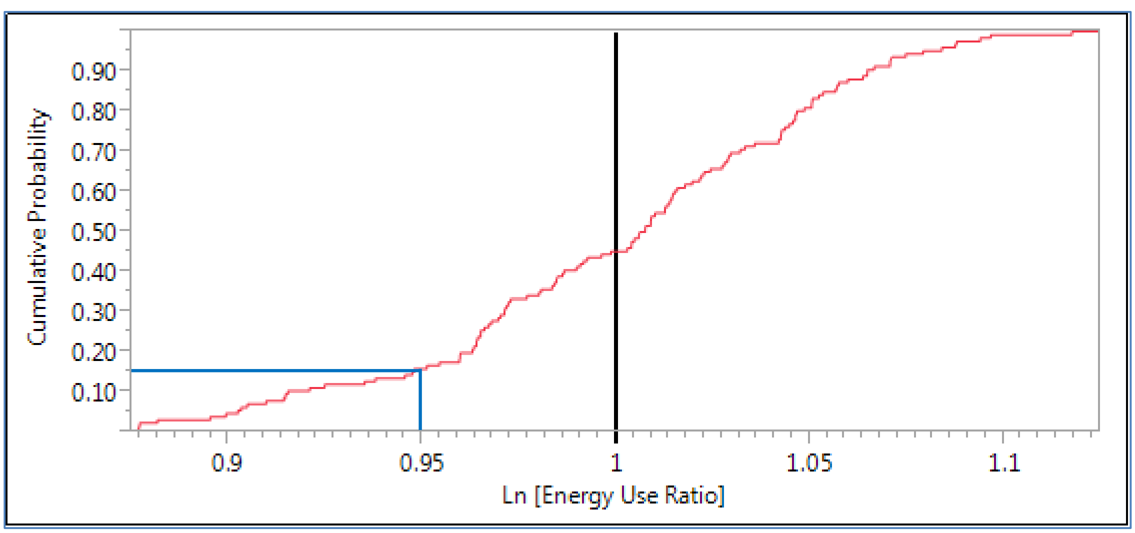


FIGURE 23: CUMULATIVE PROBABILITY GRAPH OF LN [ENERGY USE RATIO]

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APPENDIX A: PARAMETERS OF WATER UTILITY SURVEYS DATA

Production Process:

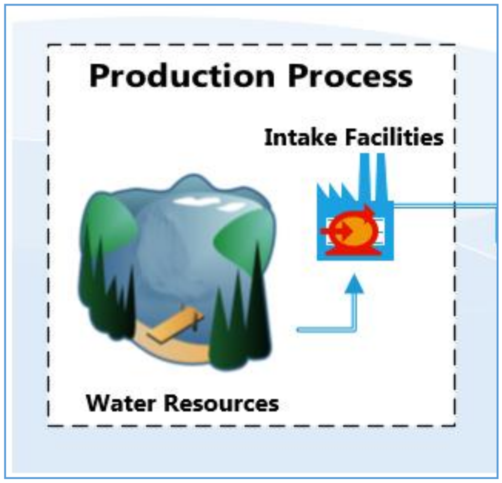

FIGURE A1: PRODUCTION PROCESS

Raw water parameter included:

1. Ground Water
    a. Number of Ground Water Sources (count)
    b. Average Ground Water Flow (MGD)
    c. Design Ground Water Flow (MGD)
    d. Maximum Ground Water Flow (MGD)

2. Surface Water:
    a. Number of Surfaces Water Sources (count)
    b. Average Surface Water Flow (MGD)
    c. Design Surface Water Flow (MGD)
    d. Maximum Surface Water Flow (MGD)

3. Purchased Water:
    a. Number of Purchased Sources (count)
    b. Average Purchased Water Flow (MGD)

4. Average Well Depth (ft)

5. Pump:
    a. Source Water Pumping HP (hp)
    b. Total Number of Pumps (count)
6. Turbidity:
    a. Average Ground Turbidity (NTU)

b. Peak Ground Turbidity (NTU)
c. Average Surface Turbidity (NTU)
d. Peak Surface Turbidity (NTU)

Energy use parameters included:

1. Production Electricity Use (kWh)
2. Production Electricity Peak (kW)
3. Production Electricity Cost ($)

Treatment Process:

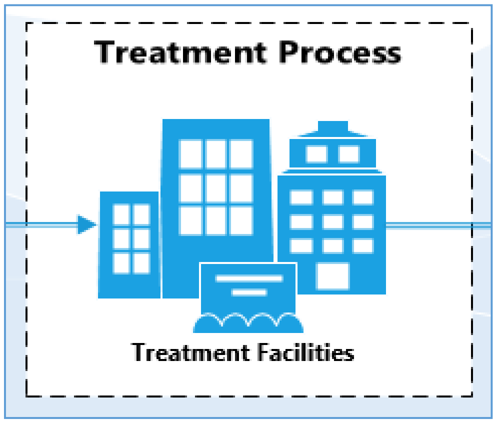

FIGURE A2: TREATMENT PROCESS

Treatment objective parameters included:

1. Algae Control (Y/N)
2. Disinfection (Y/N)
3. Oxidation (Y/N)
4. Iron Removal (Y/N)
5. Manganese Removal (Y/N)
6. Taste/Odor Control (Y/N)
7. TOC Removal (Y/N)
8. Particulate/Turbidity Removal (Y/N)
9. Softening (Y/N)
10. Recarbonation (Y/N)
11. Organic (Y/N)
12. Inorganic (Y/N)
13. Radionuclide (Y/N)

Treatment process parameters included:

1. Aeration (Y/N)
2. Ultraviolet (Y/N)
3. Ozone (Y/N)
4. Clarification:
    a. Upflow Clarification (Y/N)
    b. Gravity Clarification (Y/N)
    c. Dissolved Air Floatation Clarification (Y/N)
5. Flocculation (Y/N)
6. Filtration:
    a. Direct Filtration (Y/N)

b. Slow Sand Filtration (Y/N)
c. Dual Stage Filtration (Y/N)
d. Rapid Rate Filtration (Y/N)
e. Diatomaceous earth Filtration (Y/N)
f. Pressure Filtration (Y/N)

7. Membranes:
    a. Reverse Osmosis Membrane (Y/N)
    b. Microfiltration Membrane (Y/N)
    c. Ultrafiltration Membrane (Y/N)
    d. Nanofiltration Membrane (Y/N)
8. Number of Treatment Plants (count)

Residual handling parameters included:

1. No Treatment (Y/N)
2. Gravity Thickening (Y/N)
3. Mechanical Dewatering (Y/N)
4. Centrifuge (Y/N)
5. Residual Pressure Filtration (Y/N)
6. Vacuum Filtration (Y/N)
7. Belt Press (Y/N)
8. Plate & Frame Press (Y/N)
9. Non-Mechanical Dewatering (Y/N)
10. Lagoon dewatering thickening (Y/N)
11. Sand Drying Bed (Y/N)
12. Freezing and Thawing (Y/N)
13. Total Average Daily Residuals (lb/day)

Energy use parameters included:

1. Treatment Electricity Use (kWh)
2. Treatment Electricity Peak (kW)
3. Treatment Electricity Cost ($)

Distribution Process:

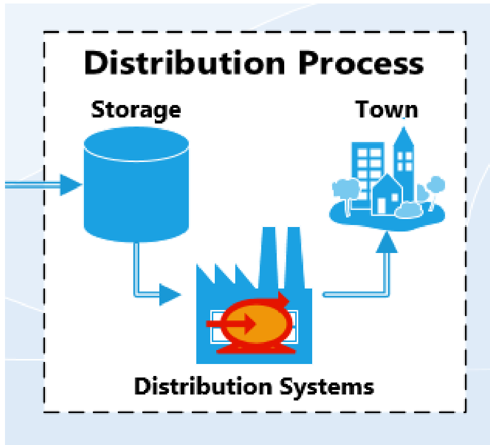

FIGURE A3: DISTRIBUTION PROCESS

Distribution parameters included:

1. Service Area:
    a. Population of Service Area (count)
    b. Size of Service Area (SQM)
    c. Length of Water Mains (miles)
    d. Number of Distribution Zones (count)
    e. Total Storage Volume (MG)
    f. Elevation:
        i. High Elevation (ft)
        ii. Low Elevation (ft)
2. Pump:
    a. Distribution Pumping HP (hp)
    b. Number of Distribution Pumps (count)
    c. Average Distribution Pressure (PSI)

Energy use parameters included:

1. Distribution Electricity Use (kWh)
2. Distribution Electricity Peak (kW)
3. Distribution Electricity Cost ($)

Overall water utility as a whole:

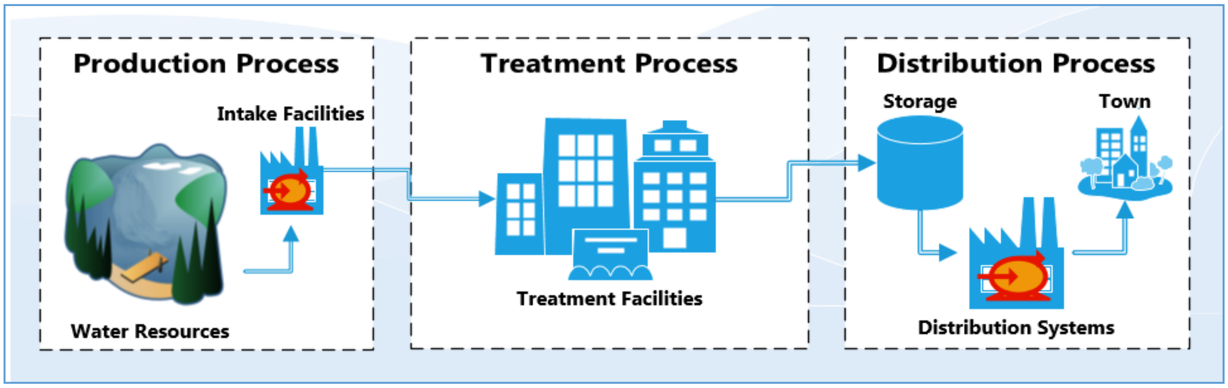

FIGURE A4: OVERALL WATER UTILITY AS A WHOLE

General parameters included:

1. Unaccounted for Treated Water (%)
2. Total Building Area (SQFT)
3. Engine Driven Pumps (Y/N)
4. Engine Driven Pump HP (hp)
5. Engine Driven Pump Fuel Type
6. Regularly Checked Utility Bills
7. Extraordinary Events (Y/N)
8. Additional Comments (Comment)
9. Total Average Flow (MGD)
10. Average raw turbidity (NTU)
11. Peak raw turbidity (NTU)
12. Treatment for metals (iron mang) (Y/N)
13. Treatment for contaminates (organic inorganic radon) (Y/N)
14. Difference between highest and lowest system elevation (ft)
15. Total system hp (hp)

Energy use parameters included:

1. Total Electricity Use (kWh)
2. Total Electricity Peak (kW)
3. Total Electricity Cost ($)
4. Natural Gas Use (Therms)
5. Natural Gas Cost ($)
6. Purchased Energy (Y/N)
7. Purchased Energy Source (Amount)
8. Amount of Purchased Energy (kBtu)
9. Purchased Energy Cost ($)