Hopping Green & Sams
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Writer's Direct Dial No.
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February 19, 2018

BY ELECTRONIC FILING

Carlotta S. Stauffer, Director
Office of Commission Clerk
Florida Public Service Commission
2540 Shumard Oak Boulevard
Tallahassee, FL 32399

Re: Docket Nos. 20170266-EC and 20170267-EC

Dear Ms. Stauffer:

Enclosed for filing on behalf of Seminole Electric Cooperative, Inc., and Shady Hills Energy Center, LLC, are electronic copies of the following:

- Rebuttal Testimony of **David Kezell** and Exhibit Nos. __ (DK-5 through DK-8);
- Rebuttal Testimony of **Kyle D. Wood** and Exhibit Nos. __ (KDW-2 through KDW-5);
- Rebuttal Testimony of **Tao Hong, Ph.D**., and Exhibit Nos __ (TAO-1 and TAO-2); and
- Rebuttal Testimony of **Alan S. Taylor**.

Please acknowledge receipt and filing of the above by return email or other means. If you have any questions concerning this filing, please contact me at 425-2359.

Thank you for your assistance in connection with this matter.

Very truly yours,

HOPPING GREEN AND SAMS, P.A.

By: ______________________

Counsel for SEMINOLE ELECTRIC COOPERATIVE, INC., and SHADY HILLS ENERGY CENTER, LLC.

BEFORE THE FLORIDA PUBLIC SERVICE COMMISSION

DOCKET NOS. 20170266-EC and 20170267-EC

IN RE: PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., FOR DETERMINATION OF NEED FOR SEMINOLE COMBINED CYCLE FACILITY

IN RE: JOINT PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., AND SHADY HILLS ENERGY CENTER, LLC., FOR DETERMINATION OF NEED FOR SHADY HILLS COMBINED CYCLE FACILITY

REBUTTAL TESTIMONY OF:

DAVID KEZELL

BEFORE THE PUBLIC SERVICE COMMISSION

SEMINOLE ELECTRIC COOPERATIVE, INC.

REBUTTAL TESTIMONY OF DAVID KEZELL

DOCKET NOS. 20170266-EC and 20170267

FEBRUARY 19, 2018

Q. Please state your name and address.

A. My name is David Kezell. My business address is 16313 North Dale Mabry Highway, Tampa, Florida 33688-2000.

Q. Have you previously submitted direct testimony in this proceeding?

A. Yes.

Q. Are you sponsoring any exhibits to your rebuttal testimony?

A. Yes. I am sponsoring the following exhibits, which were prepared by me or under my supervision and are attached to this rebuttal testimony:

- Exhibit No. __ (DK-5) - Excerpts from Site Certification Application for DBEC;
- Exhibit No. _ (DK-6) - Excerpt from DBEC Air Permit;
- Exhibit No. __ (DK-7) - Excerpt from SCCF draft Air Permit; and
- Exhibit No. __ (DK-8) - USDOE/EIA report entitled "Capital Cost Estimates for Utility Scale Electricity Generating Plants" (appendices omitted).

Q. What is the purpose of your rebuttal testimony?

A. The purpose of my testimony is to rebut Quantum Pasco Power, L.P.'s witness Dr. Sotkiewicz' claim, at pages 22 through 24 of his testimony, that Seminole's projected cost for the Seminole Combined Cycle Facility ("SCCF") is "unreliable."

Q. Please summarize your rebuttal testimony.

A. I am confident that Seminole's projected cost for the SCCF is more than adequate to execute the project because it is based in large part on a fixed price contract for power island equipment and an anticipated fixed price contract for engineering, procurement and construction ("EPC") services. In attempting to question Seminole's cost projection by comparing it to estimates for FPL's Dania Beach Energy Center ("DBEC") and other estimates for generic units, Dr. Sotkiewicz fails to recognize that costs for individual combined cycle projects necessarily vary due to a number of company-specific, design-specific, and site-specific factors. Dr. Sotkiewicz provides no valid reason to doubt the accuracy of the reported SCCF installed cost estimate.

Q. What was your involvement in the development of the projected costs for the SCCF discussed in Dr. Sotkiewicz's testimony?

A. As Seminole's Director of Engineering and Capital Development, I was responsible for developing the projected costs for the SCCF that are presented in section 4.1.10 of Seminole's Need Study (Exhibit No. __ (MPW-2)) and discussed in Dr. Sotkiewicz's testimony.

Q. Please describe your experience in developing projected costs for electric generating facilities.

A. Seminole regularly establishes cost estimates for various electric generating facilities as part of an on-going effort to stay abreast of industry developments and evaluate potential future projects. We utilize various cost estimating techniques ranging from estimates generated from Thermoflow, Inc. software packages to specifically commissioned estimates prepared by power engineering consulting organizations. We have also worked directly with various EPC firms to get indicative estimates or to check the accuracy of estimates that we have already generated.

I have personally been involved in project cost estimating for over 25 years. Prior to joining Seminole, I was responsible for the construction management arm of a multi-national consulting engineering company. For eight years, I was regularly responsible for generating or reviewing cost estimates for power facilities in this country and abroad.

Q. How did you develop the projected costs for the SCCF?

A. The cost estimate for the SCCF started with indicative estimates from organizations like Fluor and Kiewit Power Engineers. We later obtained an all-in EPC estimate developed by the construction arm of Black & Veatch. Seminole added its own project development and other Owner's cost to this estimate to come up with early versions of what became the SCCF project cost. As we bid and contracted for power island equipment, we substituted the actual contract value for the estimated value for this cost element. The competitive bidding process for the EPC work for SCCF has resulted in pricing that is considered very accurate. Several small scope items are still in the process of being finalized but we are confident that the current EPC price is within one percent of what the eventual agreed-upon contract price will be. In this fashion, Seminole has incrementally removed uncertainty in the estimate and our Direct Construction Cost and Total Installed Cost numbers have been made increasingly accurate over a period of more than two years. The power island equipment and EPC contracts together will comprise approximately 80% of the SCCF Total Installed Cost.

Q. On page 22 of his testimony, Dr. Sotkiewicz states that FPL's proposed Dania Beach Energy Center ("DBEC") is "essentially the same unit" as the SCCF and "must be considered a good yardstick" to compare with Seminole's projected costs for the SCCF. Do you agree with those assertions?

A. No, I do not. Although both the SCCF and DBEC will utilize similar GE Frame 7H combustion turbine technology, it is not appropriate to assume that the costs of the two projects should be the same. That is because the combustion turbines themselves may differ in their performance and costs for individual combined cycle projects will vary due to a number of company-specific, design-specific, and site-specific factors.

Q. On page 22 of his testimony, Dr. Sotkiewicz compares the $764/kW value for DBEC with a $648/kW value for SCCF. Are these the most appropriate comparison points?

A. No, the value he calculated for SCCF does not create an apples-to-apples comparison with the DBEC value. The $764/kW value for DBEC is derived from an anticipated installed cost of $888M divided by the plant's anticipated **summer** output of 1,163 MW; whereas the $648/kW value cited for the SCCF was calculated based on the SCCF's anticipated winter output. For a true apples-to-apples comparison with DBEC, the summer output value should be used for the SCCF. In other words, the anticipated installed cost of $727M should be divided by the plant's anticipated **summer** output of 1,108 MW resulting in a value of $656/kW. Using this value, the SCCF estimate is $108/kW or 14.2% lower than the DBEC estimate.

Q. Have you identified any project-specific factors that may account for the disparity in projected costs for the SCCF and DBEC?

A. Yes. A cursory perusal of publicly available information regarding the DBEC reveals many significant project differences that can adequately account for the disparity in the $/kW values for DBEC and SCCF. These differences are summarized as follows:

- **<u>Allowance for Funds Used During Construction</u> ("AFUDC") -** A large and obvious difference between the cost estimates for the two facilities is in the anticipated AFUDC or "allowance for funds used during construction." As shown on page 7-1 of FPL's Site Certification Application ("SCA"), which is attached as page 9 of Exhibit No. __ (DK-5), DBEC anticipates a value of $103 million while SCCF anticipates $45 million for a difference of $58 million. In $/kW terms, the DBEC Schedule 9 attached to Dr. Sotkiewicz's testimony indicates a value of

$89/kW while the SCCF's Schedule 9 provided in response to Staff discovery indicates a value of $40/kW. This item alone accounts for $49/kW or more than 45% of the $108/kW differential between the two plants. This discrepancy is largely due to the fact that FPL's projected AFUDC includes both interest during construction ("IDC") and a return on equity ("ROE") component. Because Seminole is not an investor-owned utility, the projected AFUDC for the SCCF only includes IDC; it does not include an ROE component.

- **Dual-Fuel vs. Single Fuel Design** -The DBEC is a dual fuel facility (natural gas backed up by fuel oil) while the SCCF is a single fuel facility (natural gas only). DBEC has existing fuel oil tanks but will require other items to deliver and combust it that will not be required by SCCF. I estimate that the difference in cost for adding the dual fuel firing capability (fuel oil forwarding pumps, combustion turbine modifications, controls modifications, etc.) at DBEC is approximately $7 million.
- **Differences in Gas Turbines** - The DBEC's output is approximately 55-60 MW higher than SCCF. The nominal generating capacity of each of the DBEC gas turbines is 430 MW, while the nominal generating rate for each of the SCCF gas turbines is 384 MW. As shown on page 8 of the DBEC Air Permit No. PSD-FL-442, which is attached as Exhibit No. __ (DK-6), the heat rate for the DBEC is 4,015.4 MMBtu/hr on natural gas. By comparison, as shown on page 7 of the SCCF draft Air Permit No. PSD-FL-443 , which is attached as Exhibit No. __ (DK-7), the heat rate for the SCCF is 3,514 MMBtu/hr on natural gas. The higher heat input into the DBEC gas turbines will require the DBEC heat recovery steam

generators ("HRSGs") and the entire steam production and condensing system to be designed and constructed to allow for the greater quantity of steam production available from the exhaust gasses. This difference in heat input and resultant steam output would likely result in more structural steel supporting the HRSGs, more alloy steel heat transfer tubing in the HRSGs, a larger steam turbine, a larger condenser, and commensurately larger boiler feedwater and condensate pumping and piping systems. I estimate the increased cost for DBEC to be approximately $10 million.

- **Construction Schedule -** The DBEC is anticipated to start construction in 2020 and be commercially operable in June, 2022 for a maximum apparent construction period of 30 months. The SCCF construction period allows for up to 36 months. This relatively faster schedule at DBEC increases the contractor's schedule performance risk and of having liquidated damages assessed for late delivery of the completed plant. Some increased profit margin will probably be included in the EPC pricing for DBEC relative to SCCF to account for this increased schedule performance risk.
- **Per Diem Costs -** Site management professionals and some quantity of craft laborers will likely be brought in from a significant distance for both projects. These "travelers" are typically compensated in part with an appropriate per diem to cover their housing, meal and incidental expenses. A review of the U.S. Government's standard General Service Administration ("GSA") rates (https://www.gsa.gov/travel/plan-book/per-diem-rates/per-diem-rates-lookup) for both areas reveals that the average GSA per diem cost for the Fort Lauderdale (DBEC) area is $216/day and the same cost for the Palatka (SCCF) area is $144/day for a differential of

$72/day. DBEC anticipates an average of 290 workers throughout its construction period. If half of that number of workers receive per diem for two years at both sites, the resultant difference in per diem cost between DBEC and SCCF would be $72/day * 145 people * 730 days = $7.6M. The number of people and the durations could be higher. The actual per diems paid to the workers will likely be lower than the GSA rates, however the difference in living costs between the two locations is significant.

- **Demolition of Existing Infrastructure** - There are two existing 2x1 combined cycle power plants in the location where the DBEC is planned to be constructed. Demolition of 4 combustion turbines, four HRSGs, four exhaust stacks, two steam turbine generators, two condensers and all of their appurtenant equipment, buildings and underground facilities will be required for DBEC. The SCCF is planned to be constructed on property that will simply require the removal of trees, grubbing and grading. Photographs available on maps.google.com show that the FPL site has an additional twelve simple cycle combustion turbines and all of their appurtenant equipment that will also have to be removed or demolished to make room for the facility envisioned in the DBEC renderings. The cost of removing this substantial installation may also be included in the DBEC estimate.
- **Site Differences -** The DBEC is located in a highly developed, congested urban/suburban area with limited open space on the property for construction laydown. In fact, the DBEC will utilize multiple discontiguous portions of land on the existing FPL property (SCA, Figure 5.4-1) for laydown. SCCF's single laydown area will allow for easier on-

site fabrication and construction coordination. The probability of double or triple-handling of delivered material and equipment at DBEC is higher than at SCCF. Furthermore, most of the DBEC laydown areas are in AE or AH flood zones which will require additional fill material (SCA, page 5-2) and land preparation which will not be required at SCCF.

- **Construction Parking -** It is not clear that construction parking at DBEC will be onsite at all. If not, craft personnel will have to be bussed or otherwise provided with transportation from their staging/parking area to the site. This circumstance, if necessary, would result in not only the transportation cost but likely also in decreased worker productivity with its resultant cost impact. Craft parking is available onsite at SCCF.
- **Environmental Mitigation -** The existing FPL facility supports important habitat for the threatened West Indian Manatee population in the area. FPL is planning to take steps to maintain the facility's capability as a warm water manatee refuge. In fact, as shown on page 11 of Exhibit No. ___ (DK-5), part of the industrial wastewater permit application included in the DBEC SCA application states that "FPL will construct a thermal refuge to protect manatees seeking warm water during cold weather conditions. The refuge will be available during the Unit 7 project construction phase, when the thermal discharge from the plant is temporarily discontinued and critical cold weather conditions are possible." Providing such a thermal refuge, with its associated costs, will not be required for SCCF.
- **Cooling Water Infrastructure -** The DBEC facility will require cooling water interconnections with associated valves and piping to both the existing on-site cooling system and a new supplemental cooling tower.

> The SCCF will connect to only one cooling system, a new cooling tower. The relatively greater complexity of the DBEC cooling water system will add cost that SCCF will not experience.

Q. Is the information you cited from the Site Certification Application ("SCA") for the DBEC and the various air permits publicly available?

A. Yes. The SCA for the DBEC is readily available to the public at the website of the Florida Department of Environmental Protection's ("FDEP's") Siting Office (http://publicfiles.dep.state.fl.us/Siting/Outgoing/FPL_Lauderdale_PA89-26/Dania_Beach_Energy_Center/). Likewise, the air permitting materials are publicly available through a search function located on the website of FDEP's Division of Air Resources Management (https://fldep.dep.state.fl.us/air/emission/apds/default.asp).

Q. On page 23 of his testimony, Dr. Sotkiewicz refers to "the installed cost of new advanced combined cycle plants reported by the U.S. Energy Information Administration ('EIA')" in support of his suggestion that "the cost of the SCCF facility seem[s] quite low relative to other similarly situated projects." Do you believe that the EIA figure is a valid point of comparison?

A. No. The U.S. EIA estimate of $1000/kW is a broad-brushed generic estimate typically used for comparisons between different generating plant types. As stated in the excerpt from the EIA's report attached as Exhibit No. ___ (DK-9):

"The estimates provided in this report are representative of a generic facility located in a region without any special issues that would alter its cost. However, the cost of building power plants in different regions of the United States can vary significantly." (Emphasis added).

Although the EIA report includes some location-based cost adjustments for certain areas, including Tallahassee and Tampa, these adjustments do not account for the type of project-specific impacts that I discussed previously. As clearly demonstrated by the DBEC/SCCF comparison, location and other project-specific costs do vary substantially. The power equipment and EPC markets are also healthy, competitive markets that respond quickly to market conditions with appropriate price adjustments. Furthermore, the EIA estimate of $1000/kW was originally based upon significantly smaller power plants that had a lower power output than current advanced class combined cycle facilities. The higher output of modern facilities without a commensurate increase in pricing has resulted in the $1000/kW estimate being higher than current advanced class combined cycle market conditions would support and of dubious current value.

Q. On page 23 of his testimony, Dr. Sotkiewicz also refers to estimates of smaller combined cycle units that Seminole included in its 2017 Ten Year Site Plan. Do you consider those figure to be valid points of comparison?

A. No. Seminole's 2017 Ten Year Site Plan estimates of $942/kW and $980/kW for facilities at the Seminole Generating Station ("SGS") and an unnamed location respectively were based upon 1x1 configurations with summer output levels of 593 MW. The corresponding construction cost for these facilities is approximately $559 million and $581 million respectively, with the difference being accounted for in greater uncertainty regarding the cost of linear facilities at the unnamed site. A 1x1 configuration is inherently more expensive on a $/kW basis for two simple reasons: First, the contractor's costs for engineering, mobilization, demobilization, etc. are very similar for either 1x1 or 2x1 configurations. Therefore, these costs are spread across a lesser amount of megawatts for the 1x1 configuration. Second, a 2x1 facility is benefitted by several cost efficiencies. For example, as for a 1x1, it still only requires one steam turbine generator, one condenser, and one cooling tower. These items are larger for a 2x1 but their costs do not double. These previously anticipated generic facilities and the proposed SCCF differ little in their configuration but substantially in their output. This dramatically increased output of the SCCF is the primary driver of the significant difference in the $/kW values. Further reducing the SCCF $/kW estimate is the well-documented increased modularity of the advanced class 7HA.02 turbines. General Electric succeeded in making a step change reduction in the complexity of erecting these new models by manufacturing and delivering them in discrete modules. The generic models were based upon earlier, smaller gas turbine technology that does not bring this added modularity benefit. This difference in technology has resulted in reduced erection costs for the SCCF that further reduce the $/kW ratio for facilities based upon these large combustion turbines.

Q. Does Dr. Sotkiewicz cite to any valid reason to question Seminole's projected costs for the SCCF?

A. No. I am confident that the anticipated construction and installed costs as presented for the SCCF in the Petition for Determination of Need and in the associated Schedule 9s are accurate. There are sound reasons for the differences in the $/kW values discussed herein and Dr. Sotkiewicz provides no valid reason to doubt the accuracy of the reported SCCF installed cost estimate.

Q. Does this conclude your testimony?

A. Yes.

Dania Beach Energy Center

SITE CERTIFICATION APPLICATION

Volume I of III

July 2017

FPL

SITE CERTIFICATION APPLICATION
DANIA BEACH ENERGY CENTER

VOLUME I OF III

Submitted by:

Florida Power & Light Company
700 Universe Boulevard
Juno Beach, Florida 33408

July 2017

17-73823

Kennard F. Kosky, P.E.
Professional Registered Engineer No. 14996

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***Board of Professional Engineers**
Certification of Authorization No. 00001670

KENNARD F. KOSKY
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LICENSE
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STATE OF
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PROFESSIONAL ENGINEER

VOLUME I

Table of Contents

List of Appendices

7.0 ECONOMIC AND SOCIAL EFFECTS OF PLANT CONSTRUCTION AND OPERATION

The purpose of this chapter is to identify the direct and indirect economic costs and social effects of the Project based on both temporary (construction) and long-term (operation) time periods.

Direct effects are those that are the result of the construction or operation of the DBEC. Indirect effects are those that are the result of changes in the livelihood of the people and business interests in the vicinity of a project, such as increased spending by construction and operation personnel. Many of these effects are difficult to measure and qualitative assumptions are often made to assess the relative values of anticipated costs and benefits.

This chapter is divided into two parts: benefits and costs. Section 7.1 addresses the economic and social benefits of the Project, including analyses of the direct and indirect effects of construction and operation of DBEC. Section 7.2 addresses the economic and social costs of the Project and includes analyses of the temporary and long-term indirect costs involving construction and operation of DBEC. An analysis of the fiscal and economic impacts of the DBEC is provided in Appendix 10.7.3. All costs and benefits are based on 2017 dollar values unless otherwise indicated.

7.1 Economic and Social Benefits

The DBEC is anticipated to benefit the City of Dania Beach, Broward County, and the State of Florida by providing significant economic output, requiring relatively few costs accrued to the local government, and creating a positive downstream effect spurring community growth and opportunity throughout the region.

Direct and indirect economic benefits from construction include construction workforce jobs, purchase and rental of equipment and materials, housing and living expenses for construction workers, and indirect employment. Direct and indirect economic benefits from operation include capital expenditures, operation and maintenance expenditures, employment and property tax revenues.

7.1.1 Economic Benefits

FPL estimates that the total Project capital cost will be approximately $888 million to modernize the existing power plant. Principal components include the power block ($764 million); transmission interconnection and integration ($21 million); and allowance for funds used during construction ($103 million).

7.1.1.1 Benefits of Construction

Onsite construction activities of DBEC are anticipated to begin in 2020 and conclude in mid-2022. The construction activities are anticipated to result in a total economic output of approximately $310 million

Form 1 Attachment 2

Compliance with Antidegradation Policy

The Lauderdale Plant Industrial Wastewater Facility (IWWF/NPDES) permit modification to the existing permit FL0001503 (Major) is consistent with the antidegradation permitting requirements (62-4.242 F.A.C.) and the antidegradation policy for surface water quality (62-302.300 F.A.C.) for the following reasons:

1. The Project is in the public interest, as required by Section 62-4.242(1)(b)1 F.A.C.; and the Project is clearly important to and beneficial to the public health, safety and welfare. As discussed in Public Service Commission filings, the modernization project:
    - Will provide a reliable base load generating capacity in a region where demand is the highest.
    - Will improve fuel efficiency at the Lauderdale site, and on a FPL system-wide basis.
    - Will improve the environmental profile of the Lauderdale site by lowering emission rates.
    - Will result in a lower cost supply of electricity for FPL's customers, and
    - Will create new jobs and tax revenue for Florida's economy.
2. While the facility modification will provide approximately 25 percent more power, the permit modification does not propose a new or an expanded surface water discharge. To accomplish this, the DBEC (Unit 7) cooling system will use a hybrid design -- once-through steam cycle cooling, with an auxiliary cooling system that is designed to evaporate between 0.5 percent and 1.0 percent of the once-through cooling water flow and the existing cooling pond to dissipate heat.

3. Consequently, there is no new or expanded discharge for the following reasons. First, there is no change in the industrial activity. The proposed industrial activity (i.e., fossil-fuel electric generation) is exactly the same as under the existing permit. Second, for the same meteorological conditions (rainfall, cloud cover, temperature and dew point), the annual average daily flow (AADF) from Outfall D-001 to the South Fork of New River (WBID 3277A) will be less than or equal to the existing discharge rate. Third, pollutant loads, including the thermal or heat load, from the modernized facility through D-001 to South Fork New River will be less than or equal to that of the existing facility. All existing effluent limitations for Outfall D-001 (flow, temperature, TDS, pH, copper and Whole Effluent Toxicity test results) will be met by the modernized facility.

4. The permit modification will not result in any material or measurable water quality degradation.

5. The facility modification will not adversely affect conservation of fish and wildlife, including endangered or threatened species, or their habitats. The cooling water intake withdrawal rate (design intake flow) from the Dania Cutoff canal and the intake through-screen velocity will be unchanged. As discussed above, the thermal load to the South Fork New River will not exceed the existing thermal load. Therefore, the permit modification will have no adverse effect from impingement or entrainment on fish or shellfish; and there will be no adverse effect from the thermal discharge to the South Fork New River. In other words, there will be no water quality degradation related to CWA Sections 316(a) or 316(b). Based on conditions in the existing IWWF/NPDES permit, the facility is in the process of evaluating existing impacts from

impingement and entrainment. When the Best Technology Available (BTA) determination is final, the facility will implement any required changes to address existing impacts.

6. The modernization project will not adversely affect endangered or threatened species, or their habitat. The only state or federally listed species known to occupy the waters adjacent to the modernized facility is the West Indian manatee (*Trichechus manatus*). The cooling water discharge canal and quarry areas are used by manatees as a warm-water refuge during the winter months. FPL will construct a thermal refuge to protect manatees seeking warm water during cold weather conditions. The refuge will be available during the Unit 7 project construction phase, when the thermal discharge from the plant is temporarily discontinued and critical cold weather conditions are possible.

7. The permit modification is not inconsistent with any applicable Surface Water Improvement and Management Plan that has been adopted by the South Florida Water Management District.

8. The facility does not discharge to or degrade any Outstanding Florida Waters.

Florida Department of Environmental Protection

Bob Martinez Center
2600 Blair Stone Road
Tallahassee, Florida 32399-2400

Rick Scott
Governor

Carlos Lopez-Cantera
Lt. Governor

Noah Valenstein
Secretary

PERMITTEE

Seminole Electric Cooperative, Inc.
16313 North Dale Mabry Highway
Tampa, Florida 33618

Authorized Representative:
James Frauen, Vice President of Power Delivery and Technical Services

Air Permit No. 1070025-028-AC (PSD-FL-443)
Expires: March 31, 2024
Seminole Generating Station
Facility ID No. 1070025
Seminole Combined-Cycle Facility

PROJECT

This is the final air construction permit, which authorizes the replacement of one existing coal-fired unit with a new natural gas-fired two-on-one combined cycle unit. The proposed work will be conducted at the existing Seminole Generating Station, which is an electric power plant categorized under Standard Industrial Classification No. 4911. The existing facility is in Putnam County at 890 North Highway 17 in Palatka, Florida. The UTM coordinates are Zone 17, 438.8 kilometers (km) East, and 3289.2 km North.

This final permit is organized into the following sections: Section 1 (General Information); Section 2 (Administrative Requirements); Section 3 (Emissions Unit Specific Conditions); and Section 4 (Appendices). Because of the technical nature of the project, the permit contains numerous acronyms and abbreviations, which are defined in Appendix A of Section 4 of this permit. As noted in the Final Determination provided with this final permit, only minor changes and clarifications were made to the draft permit.

STATEMENT OF BASIS

This air pollution construction permit is issued under the provisions of: Chapter 403 of the Florida Statutes (F.S.) and Chapters 62-4, 62-204, 62-210, 62-212, 62-296 and 62-297 of the Florida Administrative Code (F.A.C.). The permittee is authorized to conduct the proposed work in accordance with the conditions of this permit. This project is subject to the general preconstruction review requirements in Rule 62-212.300, F.A.C. and the preconstruction review requirements for major stationary sources in Rule 62-212.400, F.A.C. for the Prevention of Significant Deterioration (PSD) of Air Quality.

Upon issuance of this final permit, any party to this order has the right to seek judicial review of it under Section 120.68 of the Florida Statutes by filing a notice of appeal under Rule 9.110 of the Florida Rules of Appellate Procedure with the clerk of the Department of Environmental Protection in the Office of General Counsel (Mail Station #35, 3900 Commonwealth Boulevard, Tallahassee, Florida, 32399-3000) and by filing a copy of the notice of appeal accompanied by the applicable filing fees with the appropriate District Court of Appeal. The notice must be filed within 30 days after this order is filed with the clerk of the Department.

Executed in Tallahassee, Florida

(DRAFT)

For: Syed Arif, P.E., Program Administrator
Office of Permitting and Compliance
Division of Air Resource Management

CERTIFICATE OF SERVICE

The undersigned duly designated deputy agency clerk hereby certifies that this Final Air Construction Permit package was sent by electronic mail, or a link to these documents made available electronically on a publicly accessible server, with received receipt requested before the close of business on the date indicated below to the following persons.

James Frauen, SECI: JFrauen@seminole-electric.com
Chris Weber, SECI: CWeber@seminole-electric.com
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Clerk Stamp

FILING AND ACKNOWLEDGMENT FILED, on this date, pursuant to Section 120.52(7), Florida Statutes, with the designated agency clerk, receipt of which is hereby acknowledged.

(DRAFT)

SECTION 3. EMISSIONS UNIT SPECIFIC CONDITIONS (DRAFT)

A. Natural Gas-Fired Combustion Turbines with Duct-Fired HRSGs (EU Nos. 017 and 018)

This section of the permit addresses the following emissions units.

EU No.	Emission Unit Description
017	Natural Gas-Fired Combustion Turbine with Duct-Fired HRSG
018	Natural Gas-Fired Combustion Turbine with Duct-Fired HRSG

The CT proposed for the project is the General Electric (GE) 7HA.02 turbine. Each CT will utilize inlet evaporative air cooling. Emissions from each turbine will be controlled using dry low-NO_X (DLN) combustion, oxidation catalyst, and selective catalytic reduction (SCR).

Each combustion turbine generator (CTG) will have a nominal electrical output of 384 MW. Each turbine will be connected to a heat recovery steam generator (HRSG) with duct burners. Steam generated in the two HRSGs will be routed to a common steam turbine (ST), with a nominal generating capacity of 415 MW. The total gross nominal electrical generating capacity for the unit is 1,183 MW, and the net nominal generating capacity is approximately 1,050 MW.

The nominal design heat input rate to each turbine is 3,514 MMBtu/hr, based on an ambient air temperature of 59 degrees Fahrenheit (°F), evaporative cooling, 14.7 pounds per square inch (psi) pressure, the higher heating value (HHV) of the fuel, and 100% load. Each duct burner will have a nominal heat input rating of 250 MMBtu/hr (HHV).

Each HRSG will have a stack height of 199 ft and an inner stack diameter of 23.5 ft. Each stack will be equipped with continuous emissions monitoring systems (CEMS) to measure and record NO_X emissions as well as flue gas oxygen or carbon dioxide content.

{Note: Actual heat input rate varies depending upon gas turbine characteristics, ambient conditions, and inlet air cooling. A predictive emissions monitoring system (PEMS) may be used in lieu of CEMS, pending EPA approval of an alternative monitoring system petition per 40 CFR Part 75 Subpart E and 40 CFR Part 60. If the permittee wishes to change the method of compliance with the requested state-issued and NSPS NO_X limits from a CEMS to a PEMS, another air construction permit will be necessary.}

APPLICABLE STANDARDS AND REGULATIONS

1. BACT Determinations: Determination of the Best Available Control Technology (BACT) was conducted for volatile organic compounds (VOC). [Rule 62-210.200 (BACT), F.A.C.]

2. NSPS Requirements: These units shall comply with the applicable NSPS in 40 CFR 60, including: Subpart A (General Provisions), Subpart KKKK (Standards of Performance for Stationary Gas Turbines), and Subpart TTTT (Standards of Performance for Greenhouse Gas Emissions for Electric Generating Units). See Appendices Subpart A, KKKK, and TTTT of this permit. The applicant's requested standards for NO_X and the fuel sulfur specifications are as stringent as, or more stringent than, the NO_X and sulfur dioxide (SO_2) limits imposed by the applicable NSPS Subpart KKKK provisions. Some separate reporting and monitoring may be required by the individual subparts. [Rule 62-204.800(8)(b), F.A.C.; and NSPS 40 CFR 60, Subparts A, KKKK, and TTTT]

   {Permitting note: These units are not subject to the NESHAP in 40 CFR 63, Subpart YYYY, for stationary combustion turbines. Subpart YYYY does not apply to turbines that fire only natural gas.}

EQUIPMENT DESCRIPTION

3. Combustion Turbines: The permittee is authorized to install, tune, operate, and maintain two GE 7HA.02 CTs with a nominal generating capacity of 384 MW each and an inlet air filtration system with inlet air cooling. The CTs will be designed for operation in combined-cycle mode, with one shared steam turbine. The CTs may also operate in simple-cycle mode but may not bypass pollution controls. [Application 1070025-028-AC; Design]

4. Heat Recovery Steam Generators (HRSGs): The permittee is authorized to install, operate and maintain two HRSGs, associated duct burners and exhaust stacks. Each HRSG shall be designed to recover exhaust heat energy from one of the two CTGs and deliver steam to the steam turbine-electrical generator (STG). The

Florida Department of Environmental Protection

Bob Martinez Center
2600 Blair Stone Road
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Carlos Lopez-Cantera
Lt. Governor

Noah Valenstein
Secretary

PERMITTEE

Florida Power & Light Company (FPL)
700 Universe Boulevard
Juno Beach, FL 33408

Authorized Representative:
Mr. Michael W. Sole, Vice President

Air Permit No. 0110037-017-AC (PSD-FL-442)
Expires: December 31, 2023
Lauderdale Plant
Facility ID No. 0110037
Dania Beach Energy Center

PROJECT

This is the final air construction permit, which authorizes the construction and operation of a net 1,200-megawatt (MW) nominal 2-on-1 combined cycle electrical generating facility within the existing Lauderdale Site, and will be known as the "Dania Beach Energy Center" (DBEC). The proposed work will be conducted on 134 acres within the existing 392-acre Lauderdale Plant, which is an electric utilities facility categorized under Standard Industrial Classification No. 4911. The existing facility is in Broward County, 2 miles West of Ravenswood Road and can be accessed from Southwest 42nd Street and Griffin Road, Fort Lauderdale, Florida. The UTM coordinates are: Zone 17, 580.2 km East and 2883.3 km North. Latitude is: 26° 04' 05" North; and, Longitude is: 80° 11' 54" West.

This final permit is organized into the following sections: Section 1 (General Information); Section 2 (Administrative Requirements); Section 3 (Emissions Unit Specific Conditions); and Section 4 (Appendices). Because of the technical nature of the project, the permit contains numerous acronyms and abbreviations, which are defined in Appendix A of Section 4 of this permit.

STATEMENT OF BASIS

This air pollution construction permit is issued under the provisions of: Chapter 403 of the Florida Statutes (F.S.) and Chapters 62-4, 62-204, 62-210, 62-212, 62-296 and 62-297 of the Florida Administrative Code (F.A.C.). The permittee is authorized to conduct the proposed work in accordance with the conditions of this permit. This project is subject to the general preconstruction review requirements in Rule 62-212.300, F.A.C. and the preconstruction review requirements for major stationary sources in Rule 62-212.400, F.A.C. for the Prevention of Significant Deterioration (PSD) of Air Quality.

Upon issuance of this final permit, any party to this order has the right to seek judicial review of it under Section 120.68 of the Florida Statutes by filing a notice of appeal under Rule 9.110 of the Florida Rules of Appellate Procedure with the clerk of the Department of Environmental Protection in the Office of General Counsel (Mail Station #35, 3900 Commonwealth Boulevard, Tallahassee, Florida, 32399-3000) and by filing a copy of the notice of appeal accompanied by the applicable filing fees with the appropriate District Court of Appeal. The notice must be filed within 30 days after this order is filed with the clerk of the Department.

Executed in Tallahassee, Florida

Syed Arif, P.E., Program Administrator
Office of Permitting and Compliance
Division of Air Resource Management

CERTIFICATE OF SERVICE

The undersigned duly designated deputy agency clerk hereby certifies that this Final Air Construction Permit package was sent by electronic mail, or a link to these documents made available electronically on a publicly accessible server, with received receipt requested before the close of business on the date indicated below to the following persons.

Michael W. Sole, FPL: Michael.Sole@fpl.com
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Clerk Stamp

FILING AND ACKNOWLEDGMENT FILED, on this date, pursuant to Section 120.52(7), Florida Statutes, with the designated agency clerk, receipt of which is hereby acknowledged.

A. Combined Cycle Unit 7 (EU Nos. 055 & 056)

This section of the permit addresses the following emissions units.

EU No.	Emission Unit Description
055	Unit 7A – One nominal 430 MW combustion turbine with HRSG
056	Unit 7B – One nominal 430 MW combustion turbine with HRSG

CT proposed for this project is the General Electric (GE) 7HA combustion turbine. Each CT will utilize evaporative cooling and wet compression. Emissions from each turbine will be controlled using dry low-NOx (DLN) combustion and selective catalytic reduction (SCR). The nominal heat input rate to each gas turbine is 4,015.4 million British thermal units per hour (MMBtu/hour) when firing natural gas and 3,603.6 MMBtu/hour when firing distillate oil (based on a compressor inlet air temperature of 75° F, the higher heating value (HHV) of each fuel, at baseload).

Each HRSG will have a stack height of approximately 149 feet and an inner stack diameter of approximate 25.6 feet. Each stack will be equipped with a continuous emissions monitoring systems (CEMS) to measure and record NO_X emissions as well as flue gas oxygen or carbon dioxide content.

{Permitting Note: In accordance with Rule 62-212.400(PSD), F.A.C., the above emission unit is subject to Best Available Control Technology (BACT) determinations for the following pollutants: carbon monoxide (CO), particulate matter (PM/PM_{10}), sulfuric acid mist (SAM), sulfur dioxide (SO_2), and volatile organic compounds (VOC). The final BACT determinations are presented in Appendix E of this permit. These emissions units are regulated under the federal Acid Rain Program; and, NSPS Subpart A (General Provisions) and Subpart KKKK (Standards of Performance for Stationary Combustion Turbines) of 40 CFR 60, adopted and incorporated by reference in Rule 62-204.800(8)(b)82., F.A.C. The requested limits for NO_X assure compliance with Rule 62-296.570, F.A.C. (RACT).}

SHUTDOWN UNITS

1. Shutdown Units: The following units are required to permanently shut down as a part of the PSD project: Units 4 and 5 (CTs 4A, 4B, 5A, and 5B; EU Nos. 035 - 038). [Rule 62-212.400(12), F.A.C. and Application No. 0110037-017-AC]

EQUIPMENT SPECIFICATIONS

2. Combustion Turbines & HRSGs: The permittee is authorized to install, tune, operate, and maintain two GE 7HA CTs with a nominal generating capacity of 430 MW each with inlet air cooling (i.e. evaporative cooling and wet compression). The CTs will be designed for operation in combined-cycle mode with two HRSGs and one steam turbine generator and will have dual-fuel capability (natural gas and ULSD fuel oil). Each CT may also operate in simple cycle mode without the steam turbine generator. Each HRSG exhaust stack shall be approximately 149 feet tall and 25.6 feet in diameter. [Rule 62-4.070(3), F.A.C. and Application No. 0110037-017-AC]

CONTROL TECHNOLOGY

3. Combustion Technology: The permittee shall install, operate and maintain the dry-low NO_X (DLN) combustion system or its equivalent on each CT to control NO_X emissions from the CT when firing natural gas. Prior to the initial emissions performance tests required for the CT, the DLN combustors or its equivalent and automated gas turbine control system shall be tuned to achieve sufficiently low CO and NO_X values to meet the CO and NO_X limits with the additional SCR control technology described below. Thereafter, the system shall be maintained and tuned in accordance with the manufacturer's recommendations or determined best practices.
[Rule 62-4.070(3), F.A.C. and Design; Application No. 0110037-017-AC]

Independent Statistics & Analysis
U.S. Energy Information Administration

Capital Cost Estimates for Utility Scale Electricity Generating Plants

November 2016

Contents

Tables

Introduction

The current and future projected cost and performance characteristics of new electric generating capacity are critical inputs into the development of energy projections and analyses. The construction and operating costs, along with the performance characteristics of new generating plants, play an important role in determining the mix of capacity additions that will serve future demand for electricity. These parameters also help to determine how new capacity competes against existing capacity, and the response of the electric generators to the imposition of environmental controls on conventional pollutants or any limitations on greenhouse gas emissions.

EIA commissioned an external consultant to develop up-to-date cost and performance estimates for utility-scale electric generating plants for AEO2013.[1] This information allowed EIA to compare the costs of different power plant technologies on a standardized basis and was a key input enhancement to the National Energy Model System (NEMS). For the AEO 2016 development, EIA commissioned the same consultant group to update the cost and performance estimates for a select set of the technologies evaluated in the original 2012 study. This paper summarizes the results of the findings and discusses how EIA used the updated information to analyze the development of new capacity in the electric power sector.

Developing updated estimates: key design considerations

The focus of the 2016 update was to gather current information on the "overnight" construction costs, operating costs, and performance characteristics for a wide range of generating technologies.[2] The estimates were developed through costing exercises, using a common methodology across technologies. Comparing cost estimates developed on a similar basis using the same methodology is of particular importance to ensure modeling consistency.

Each technology is represented by a generic facility of a specific size and configuration, in a location that does not have unusual constraints or infrastructure requirements. Where possible, costs estimates were based on information on system design, configuration, and construction derived from actual or planned projects known to the consultant, using generic assumptions for labor and materials rates. When this information was not available, the project costs were estimated using a more generic technology representation and costing models that account for the current labor and materials rates necessary to complete the construction of a generic facility as well as consistent assumptions for the contractual relationship between the project owner and the construction contractor.

The specific overnight costs for each type of facility were broken down to include:

- **Civil and structural costs:** allowance for site preparation, drainage, the installation of underground utilities, structural steel supply, and construction of buildings on the site
- **Mechanical equipment supply and installation:** major equipment, including but not limited to, boilers, flue gas desulfurization scrubbers, cooling towers, steam turbine generators,

[1] U.S. Energy Information Administration, Updated Capital Cost Estimates for Utility Scale Electricity Generating Plants 2013
[2] The term "overnight" refers to the cost of the project as if no interest were incurred during its construction.

condensers, photovoltaic modules, combustion turbines, wind turbines, and other auxiliary equipment

- **Electrical and instrumentation and control:** electrical transformers, switchgear, motor control centers, switchyards, distributed control systems, and other electrical commodities
- **Project indirect costs**: engineering, distributable labor and materials, craft labor overtime and incentives, scaffolding costs, construction management start up and commissioning, and fees for contingency[3]
- **Owners costs:** development costs, preliminary feasibility and engineering studies, environmental studies and permitting, legal fees, insurance costs, property taxes during construction, and the electrical interconnection costs, including a tie-in to a nearby electrical transmission system

Non-fuel operations and maintenance (O&M) costs associated with each of the power plant technologies were evaluated as well. The O&M costs that do not vary significantly with a plant's electricity generation are classified as fixed, including salaries for facility staff and maintenance that is scheduled on a calendar basis. The costs incurred to generate electricity are classified as variable such as the cost of consumable materials and maintenance that may be scheduled based on the number of operating hours or start-stop cycles of the plant. The heat rates[4] were also evaluated for the appropriate technologies. It should be noted that all estimates provided in this report are broad in scope. A more in-depth cost assessment would require a more detailed level of engineering and design work, tailored to a specific site.

Findings

Table 1 summarizes updated cost estimates for generic utility-scale generating technologies, including four powered by coal, six by natural gas, three by solar energy, and one each by wind, biomass, uranium, and battery storage. EIA does not model all of these generating plant types, but included them in the study in order to present consistent cost and performance information for a broad range of generating technologies and to aid in the evaluation for potential inclusion of new or different technologies or technology configurations in future analyses.

The specific technologies represented in the NEMS model for*AEO2016* that use the cost data from this report are identified in the last column of Table 1.

Table 2 compares the updated overnight cost estimates to those developed for the 2013 report. To facilitate comparisons, the costs are expressed in 2016 dollars.[5] Notable changes include:

- **Ultra Supercritical Coal (USC) with and without carbon capture and storage (USC/CCS).** USC with carbon capture and storage was added for this study to help meet EPA's 111b new source performance standard for carbon emissions. While USC without carbon capture cannot be built under current regulations, inclusion of this technology maintains the capability to analyze policy alternatives that may exclude 111b requirements.

[3] Fees for contingency include contractor overhead costs, fees, profit, and construction.
[4] Heat Rate is a measure of generating station thermal efficiency commonly stated as Btu per kilowatthour.
[5] U.S. Energy Information Administration, Annual Energy Outlook 2016, Table 20, GDP chain-type price index

- **Conventional Natural Gas Combined Cycle (NGCC) and Advanced Natural Gas Combined Cycle (ANGCC):** The updated overnight capital cost for conventional and advanced NGCC plants remained level relative to the cost in the 2013 study. The capacity of the NGCC unit increased from 400 MW in the 2013 study to 429 MW, while the capacity of the ANGCC unit increased from 620 MW to 702 MW for ANGCC to reflect trends toward larger installations for this technology.
- **Onshore Wind**: Overnight costs for onshore wind decreased by approximately 25 percent relative to the 2013 study, primarily due to lower wind turbine prices. EIA adjusted regional cost factors for wind plants from those reported in this report for inclusion in AEO 2016[hyper link to Table 8.2]. The regional factors in this report primarily account for regional variation in labor and materials costs, but subsequent evaluation of the regional variation in wind plant costs found that other factors, such as typical plant size, may account for a larger share of the observed regional differences in cost for the wind plants.
- **Solar Photovoltaic:** The overnight capital costs for solar photovoltaic technologies decreased by 67 percent for the 20 MW fixed tilt photovoltaic systems from the costs presented in the 2013 study. Solar photovoltaic single-axis tracking systems were introduced in this report (including both a 20 MW and 150 MW system configurations). There is not a significant difference in Capital costs between fixed-tilt and single-axis-tracking systems. The overall decreases in costs can be attributed to a decline in the component costs and the construction cost savings for the balance of plant systems.

  As previously noted, costs are developed using a consistent methodology that includes a broad project scope and includes indirect and owners costs. The cost figures will not necessarily match those derived in other studies that employ different approaches to cost estimation.

EIA's analysis of technology choice in the electric power sector

EIA's modeling employs a net present value (NPV) capital budgeting methodology to evaluate different investment options for new power plants. Estimates of the overnight capital cost, fixed and variable operations and maintenance costs, and plant heat rates for generic generating technologies serve as a starting point for developing the total cost of new generating capacity. However, other parameters also play a key role in determining the total capital costs. Because several of these factors are dynamic, the realized overall capital cost for given technologies can vary based on a variety of circumstances. Five of the most notable parameters are:

- **Financing:** EIA determines the cost of capital required to build new power plants by calculating a weighted average cost of capital using a mix of macro-economic parameters determined through EIA's modeling and an assumed capital structure for the electric power industry.
- **Lead Time:** The amount of time needed to build a given type of power plant varies by technology. Projects with longer lead times increase financing costs. Each year of construction represents a year of additional interest charges before the plant is placed in service and starts generating revenue. Furthermore, plants with front-weighted construction and development profiles will incur higher interest charges during construction than plants where most of the construction expenditures occur at the end of the development cycle.

- **Inflation of material and construction costs:** The projected relationship between the rate of inflation for the overall economy and key drivers of plant costs, such as materials and construction, are important elements impacting overall plant costs. A projected economy-wide inflation rate that exceeds the projected inflation rate for materials and construction costs results in a projected decline in real (inflation-adjusted) capital costs and vice versa.
- **Resource Supply:** Technologies such as wind, geothermal, or hydroelectric must be sited in suitable locations to take advantage of the particular resource. In order to capture the site specific costs associated with these technologies, EIA develops upward sloping supply curves for each of these technologies. These curves assume that the lowest-cost, most-favorable resources will be developed first, and when only higher-cost, less-favorable sites remain, development costs will increase and/or project performance will decrease.
- **Learning by doing:** The overnight capital costs developed for the report serve as an input to EIA's long term modeling and represent the cost of construction for a project that could begin as early as 2015. However, these costs are assumed to decrease over time in real terms as equipment manufacturers, power plant owners, and construction firms gain more experience with certain technologies. The rate at which these costs decline is often referred to as the learning rate.

  EIA determines learning rates at the power plant component level, not for the power plant technology itself because some technologies share the same component types. It is assumed that the knowledge and experienced gained through the manufacture and installation of a given component in one type of power plant can be carried over to the same component in another type of plant. As an example, the experience gained through the construction of natural gas combustion turbine plants can be leveraged to influence the overall cost of building a Natural Gas Combined Cycle unit, which in part, includes the components of a combustion turbine natural gas plant. Other technologies, such as nuclear power and pulverized coal (PC) plants without CCS, do not share component systems, and their learning rates are determined solely as a function of the amount of capacity built over time.

  Technologies and their components are represented in the NEMS model at various stages of maturity. EIA classifies technologies into three such stages: mature, evolutionary, and revolutionary. The initial learning rate is evaluated for each technology. The technology classification determines how the rate of cost reduction changes as each technology progresses through the learning function. Generally, overnight costs for technologies and associated components decline at a specified rate based on a doubling of new capacity. The cost decline is fastest for revolutionary technologies and slower for evolutionary and mature technologies.[6]

[6] U.S. Energy Information Administration, Electricity Market Module Assumptions Document, Table 8.3.

> The capacity additions used to influence learning are primarily developed from NEMS results. However, external capacity additions from international projects are also included for some technologies, to account for additional learning from such projects. For power plant technologies with multiple components, the capacity additions are weighted by the contribution of each component to the overall plant construction cost.[7]

Table 3 classifies the status of each technology and component as modeled in *AEO2016*

The NEMS model also assumes that efficiency for all fossil-fueled plants improves as a result of learning by doing. The power plant heat rates provided by the consultant are intended to represent the characteristics of a plant that starts construction in 2015 referred to as "first-of-a-kind." NEMS assumes that the heat rate for all fossil fueled technologies declines over time to a level referred to as an "nth-of-a-kind" heat rate.[8] The magnitude of heat rate improvement depends on the current state of the technology, with revolutionary technologies seeing a more significant decline in heat rate than mature technologies. Heat rate improvements are independent of capacity expansion. Fixed and variable O&M are not assumed to achieve learning-related savings. The performance of wind plants, as measured by capacity factor, is also assumed to improve as a result of learning by doing.[9]

Impact of location on power plant capital costs

The estimates provided in this report are representative of a generic facility located in a region without any special issues that would alter its cost. However, the cost of building power plants in different regions of the United States can vary significantly. The report includes location-based cost adjustment tables for each technology in 64 metropolitan areas. These adjustments were made to reflect the impact of remote location costs, costs associated with seismic design that may vary by region, and labor wage and productivity differences by region. In order to reflect these costs in EIA's modeling, these adjustments were aggregated to represent the 22 Electricity Market Module regions. EIA also assumes that the development of certain technologies is not feasible in given regions for geographic, logistical, or regulatory reasons. The regional cost adjustments and development restrictions are summarized in Table 4.

Subsequent peer review of these results indicated that the regional factors used for wind plants do not adequately reflect observed regional variation of wind plant costs, which appear to be substantially determined by factors other than those considered above. In particular, EIA found a significant regional variation in typical plant size that generally correlated with regional variation in installation costs. Therefore, EIA does not use the regional factors included in this report for its analysis of wind technologies. Regional factors used for AEO 2016 and related analyses can be found in Table 8.2 of the AEO 2016 Assumptions document, and are also shown in Table 4.

[7] U.S. Energy Information Administration, Electricity Market Module Assumptions Document, Table 8.4.
[8] U.S. Energy Information Administration, AEO 2016 Cost and Performance Characteristics of New Central Station Electricity Generating Technologies, Table 8.2.
[9] U.S. Energy Information Administration, Renewable Fuels Module

Summary

The estimates provided by the consultant for this report are key inputs for EIA electric market projections, but they are not the sole driver of electric generation capacity expansion decisions. The evolution of the electricity mix in each of the 22 regions modeled in *AEO2016* is sensitive to many factors, including the projected evolution of capital costs over the modeling horizon, projected fuel costs, whether wholesale power markets are regulated or competitive, the existing generation mix, additional costs associated with environmental control requirements, and future electricity demand.

Users interested in additional details regarding these updated cost estimates should review the consultant study prepared by Leidos Engineering, LLC in Appendix B.

Table 1. Updated estimates of power plant capital and operating costs

	Plant Characteristics		Plant Costs (2016$)			
Technology	Nominal Capacity (MW)	Heat Rate (Btu/kWh)	Overnight Capital Cost ($/kW)	Fixed O&M ($/kW-yr)	Variable O&M ($/MWh)	NEMS Input
Coal						
Ultra Supercritical Coal (USC)[10]	650	8,800	3,636	42.1	4.6	N
Ultra Supercritical Coal with CCS (USC/CCS)[11]	650	9,750	5,084	70	7.1	Y
Pulverized Coal Conversion to Natural Gas (CTNG)	300	10,300	226	22	1.3	N
Pulverized Coal Greenfield with 10-15 percent	300	8,960	4,620	50.9	5	N
Pulverized Coal Conversion to 10 percent biomass –	300	10,360	537	50.9	5	Y
Natural Gas						
Natural Gas Combined Cycle (NGCC)	702	6,600	978	11	3.5	Y
Advanced Natural Gas Combined Cycle (ANGCC)[13]	429	6,300	1,104	10	2	Y
Combustion Turbine (CT)	100	10,000	1,101	17.5	3.5	Y
Advanced Combustion Turbine (ACT)	237	9,800	678	6.8	10.7	Y
Reciprocating Internal Combustion Engine (RICE)	85	8,500	1,342	6.9	5.85	N
Uranium						
Advanced Nuclear (AN)	2,234	N/A	5,945	100.28	2.3	Y
Biomass						
Biomass (BBFB)	50	13,500	4,985	110	4.2	N
Wind						
Onshore Wind (WN)	100	N/A	1,877	39.7	0	Y
Solar						
Photovoltaic – Fixed	20	N/A	2,671	23.4	0	N
Photovoltaic – Tracking	20		2,644	23.9	0	N
Photovoltaic – Tracking	150	N/A	2,534	21.8	0	Y
Storage						
Battery Storage (BES)	4	N/A	2,813	40	8	N

[10] USC coal without CCS is not compliant with 111b new source standards for carbon emissions and cannot be built in the AEO2016 forecast.
[11] Ultra Supercritical Coal with 30% CCS
[12] Represents capital cost to retrofit existing coal plants to operate with 10% biomass fuel.
[13] "Advanced"-higher capital cost with reduced operating costs

Table 2. Overnight cost comparison with 2013 estimates

	Overnight Capital Cost (2016 $/kW)		
	2016 Report	2013 report	% Difference
Coal			
Single Unit Advanced PC	N/A	$3,453	N/A
Dual Unit Advanced PC	N/A	$3,121	N/A
Single Unit Advanced PC with CCS	N/A	$5,561	N/A
Dual Unit Advanced PC with CCS	N/A	$5,026	N/A
Single Unit IGCC	N/A	$4,681	N/A
Dual Unit IGCC	N/A	$4,026	N/A
Single Unit IGCC with CCS	N/A	$7,020	N/A
Ultra Supercritical Coal (USC)	$3,636	N/A	5%[14]
Ultra Supercritical Coal with CCS (USC/CCS)	$5,084	N/A	N/A
Pulverized Coal Conversion to Natural Gas (CTNG)	$226	N/A	N/A
Pulverized Coal Greenfield with 10-15 percent biomass (GCBC)	$4,620	N/A	N/A
Pulverized Coal Conversion to 10 percent biomass Co-Firing 30 MW (CTCB)	$537	N/A	N/A
Natural Gas			
Conventional CC	$978	$976	0.3%
Advanced CC	$1,104	$1,088	1%
Advanced CC with CCS	N/A	$2,229	N/A
Conventional CT	$1,101	$1,035	6%
Advanced CT	$678	$719	(6%)
Fuel Cells	N/A	$7,562	N/A
Reciprocating Internal Combustion Engine (RICE)	$1,342	N/A	N/A
Uranium			
Dual Unit Nuclear	$5,945	$5,883	1%
Biomass			
Biomass CC	N/A	$8,702	N/A
Biomass BFB	$4,985	$4,377	12%
Wind			
Onshore Wind	$1,877	$2,354	(25%)
Offshore Wind	N/A	$6,628	N/A

[14] Comparison of costs of coal units without carbon control, despite difference in generation performance (ultra supercritical vs supercritical)

Table 2. Overnight cost comparison with 2013 estimates (cont.)

	Overnight Capital Cost (2016 $/kW)		
	2016 Report	2013 report	% Difference
Solar			
Solar Thermal	N/A	$5,390	N/A
Solar Photovoltaic (20 MW)	$2,671	$4,450	(67%)
Solar Photovoltaic (150 MW)	N/A	$4,120	N/A
Solar Photovoltaic -Tracking (20 MW)	$2,644	N/A	N/A
Solar Photovoltaic - Tracking (150 MW)	$2,534	N/A	N/A
Geothermal – Dual Flash	N/A	$6,641	N/A
Geothermal – Binary	N/A	$4,640	N/A
Municipal Solid Waste			
Municipal Solid Waste	N/A	$8,843	N/A
Hydroelectric			
Conventional Hydroelectric	N/A	$3,123	N/A
Pumped Storage	N/A	$5,626	N/A
Battery Storage (4 MW)	2,813	N/A	N/A

Table 3. Status of technologies and components modeled by EIA

	Revolutionary	Evolutionary	Mature
Pulverized Coal			X
Pulverized Coal with CCS			
- Non-CCS portion of Pulverized Coal Plant			X
- CCS	X		
Integrated Gasification Combined Cycle			
- Advanced Combustion Turbine		X	
- Heat Recovery Steam Generator			X
- Gasifier		X	
- Balance of Plant			X
Conventional Natural Gas Combined Cycle			
- Conventional Combustion Turbine			X
- Heat Recovery Steam Generator			X
- Balance of Plant			X
Advanced Natural Gas Combined Cycle			
- Advanced Combustion Turbine		X	
- Heat Recovery Steam Generator			X
- Balance of Plant			X
Advanced Natural Gas Combined Cycle with CCS			
- Advanced Combustion Turbine		X	
- Heat Recovery Steam Generator			X
- Balance of Plant			X
- CCS	X		
Conventional Natural Gas Combustion Turbine			
- Conventional Combustion Turbine			X
- Balance of Plant			X
Advanced Natural Gas Combustion Turbine			
- Advanced Combustion Turbine		X	
- Balance of Plant			X
Advanced Nuclear	X		
Biomass			
- Pulverized Coal			X
- Fuel Preparation		X	
Geothermal		X	
Municipal Solid Waste/Landfill Gas			X
Conventional Hydroelectric			X
Wind			
- Onshore/Common Components			X
- Offshore Components	X		
Solar Thermal	X		
Solar PV			
- Modules (Utility and End Use)		X	
- Utility Balance of Plant		X	

Table 4. Regional cost adjustments for technologies modeled by NEMS by Electric Market Module (EMM) region[15]

EMM Region	PC	IGCC	PC w/CCS	Conv. CT	Adv. CT	Conv. CC	Adv. CC	Adv. CC w/CCS	Fuel Cell	Nuclear	Biomass	MSW	On-shore Wind	Off-shore Wind	Solar Thermal	Solar PV
1 (ERCT)	0.91	0.92	0.92	0.93	0.95	0.91	0.92	0.9	0.96	0.96	0.93	0.93	0.95	0.92	0.86	0.87
2 (FRCC)	0.92	0.93	0.94	0.93	0.93	0.91	0.92	0.92	0.97	0.97	0.94	0.94	N/A	N/A	0.89	0.9
3 (MROE)	1.01	1.01	0.99	0.99	1.01	0.99	0.99	0.97	0.99	1.01	0.99	0.98	0.99	0.97	N/A	0.96
4 (MROW)	0.95	0.96	0.96	0.98	1.00	0.97	0.97	0.96	0.98	0.98	0.96	0.96	1.03	1.01	N/A	0.95
5 (NEWE)	1.1	1.09	1.05	1.16	1.2	1.16	1.15	1.08	1.01	1.05	1.04	1.02	1.06	1.03	N/A	1.03
6 (NYCW)	N/A	N/A	N/A	1.63	1.68	1.68	1.66	1.5	1.14	N/A	1.26	1.26	N/A	1.29	N/A	N/A
7 (NYLI)	N/A	N/A	N/A	1.63	1.68	1.68	1.66	1.5	1.14	N/A	1.26	1.26	1.25	1.29	N/A	1.45
8 (NYUP)	1.11	1.1	1.05	1.17	1.22	1.16	1.16	1.06	1.00	1.07	1.03	1.00	1.01	0.99	N/A	0.98
9 (RFCE)	1.15	1.14	1.09	1.21	1.25	1.21	1.21	1.12	1.02	1.08	1.07	1.03	1.05	1.03	N/A	1.05
10 (RFCM)	0.98	0.98	0.98	1.01	1.02	1.00	1.00	0.99	0.99	0.99	0.98	0.98	1.00	0.98	N/A	0.97
11 (RFCW)	1.05	1.04	1.02	1.05	1.06	1.04	1.04	1.02	1.00	1.03	1.02	1.00	1.02	1.01	N/A	1.00
12 (SRDA)	0.92	0.93	0.93	0.95	0.96	0.93	0.93	0.92	0.97	0.96	0.93	0.94	0.96	1.00	N/A	0.89
13 (SRGW)	1.07	1.06	1.05	1.05	1.05	1.06	1.05	1.04	1.02	1.03	1.03	1.03	1.04	1.00	N/A	1.05
14 (SRSE)	0.92	0.93	0.93	0.95	0.97	0.93	0.94	0.92	0.97	0.96	0.93	0.94	0.96	0.93	N/A	0.89
15 (SRCE)	0.93	0.94	0.94	0.94	0.95	0.93	0.93	0.92	0.97	0.97	0.94	0.94	0.96	1.00	N/A	0.89
16 (SRVC)	0.89	0.91	0.91	0.91	0.93	0.88	0.89	0.88	0.96	0.95	0.91	0.91	0.95	0.92	N/A	0.84
17 (SPNO)	0.98	0.99	0.98	1.00	1.01	0.99	0.99	0.98	0.99	0.99	0.98	0.98	1.02	N/A	0.97	0.97
18 (SPSO)	0.98	0.99	0.98	1.00	1.01	0.99	0.99	0.98	0.99	0.99	0.98	0.98	1.02	N/A	0.97	0.97
19 (AZNM)	1.00	1.00	0.99	1.03	1.04	1.02	1.02	1.00	0.99	1.00	1.00	0.99	1.03	1.00	0.99	0.99
20 (CAMX)	N/A	N/A	1.12	1.24	1.29	1.25	1.24	1.15	1.03	N/A	1.08	1.06	1.12	1.05	1.13	1.11
21 (NWPP)	1.01	1.01	1.00	1.02	1.03	1.01	1.01	0.99	0.99	1.01	1.00	0.98	1.05	1.02	0.99	0.99
22 (RMPA)	0.99	0.99	0.97	1.02	1.05	1.01	1.01	0.96	0.98	1.01	0.97	0.95	1.03	N/A	0.93	0.93

Note: Geothermal and Hydroelectric plants are not included in the table because EIA uses site specific cost estimates for these technologies which include regional factors.

[15] The regional tables in the report were aggregated to the appropriate Electricity Market Module region in order to represent regional cost factors in NEMS

BEFORE THE FLORIDA PUBLIC SERVICE COMMISSION

DOCKET NOS. 20170266-EC and 20170267-EC

IN RE: PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., FOR DETERMINATION OF NEED FOR SEMINOLE COMBINED CYCLE FACILITY

IN RE: JOINT PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., AND SHADY HILLS ENERGY CENTER, LLC., FOR DETERMINATION OF NEED FOR SHADY HILLS COMBINED CYCLE FACILITY

REBUTTAL TESTIMONY OF:

KYLE D. WOOD

BEFORE THE PUBLIC SERVICE COMMISSION

SEMINOLE ELECTRIC COOPERATIVE, INC.

REBUTTAL TESTIMONY OF KYLE D.WOOD

DOCKET NOS. 20170266-EC and 20170267-EC

FEBRUARY 19, 2018

Q. Please state your name and address.

A. My name is Kyle Wood. My business address is 16313 North Dale Mabry Highway, Tampa, Florida 33688-2000.

Q. Have you previously submitted direct testimony in this proceeding?

A. Yes.

Q. Are you sponsoring any exhibits to your rebuttal testimony?

A. Yes. I am sponsoring the following exhibits, which were prepared by me or under my supervision and are attached to this rebuttal testimony:

- Exhibit No. __ (KDW-2) - Seminole's current forecasting methodology and model/variable selection process;
- Exhibit No. __ (KDW-3) - Comparison of historical error rates based on Sotkiewicz approach;
- Exhibit No. __ (KDW-4) - Historical Seminole error rates based on corrected Sotkiewicz approach; and
- Exhibit No. __ (KDW-5) – Seminole 2017 Load Forecast Error Analysis.

Q. What is the purpose of your rebuttal testimony?

A. The purpose of my testimony is to rebut Quantum Pasco Power, L.P.'s witness Dr. Sotkiewicz' claims regarding Seminole's load forecasting error.

Q. On page 11 of his direct testimony, Dr. Sotkiewicz states that "[t]he Commission should invite Seminole to correct its forecasting methodologies …." Has Seminole made any improvements to its forecasting methodology over the past few years?

A. Yes. In 2014, Seminole invested in state-of-the art statistical analysis software to move load forecasting data and models from "SAS on the mainframe" to "SAS on Windows PC." This improvement in technology allowed Seminole to re-examine and enhance the load forecasting process, including forecast methodology.

In January 2015, Seminole ended its practice of forecasting usage-per consumer and transitioned to modeling and forecasting total energy requirements. Seminole also ended its practice of modeling and forecasting load factor in order to calculate demand based on the product of usage per consumer, forecasted consumers and forecasted load factor. Seminole's new methodology is to model and forecast demand as a dependent variable in an econometric model with regressors including load factor, weather, and economic growth trends. In addition to updating technology and methodology, Seminole also invested in acquiring weather data from 25 weather stations in Florida and Georgia, an increase from only 8 stations previously employed.

The weather station selection process was also updated to a state-of-the-art weather station selection methodology.

In the 2016 load forecast study, Seminole joined Itron's Energy Forecasting Group. The aim was to incorporate Itron data (based on the EIA National End-Use Modeling System) into energy and demand models to control for trends in building shell efficiency, end-use appliance saturation, and efficiency. In order to do this, Seminole incorporated Itron's Statistically Adjusted End-use (SAE) approach into Seminole's own methodology. Seminole adjusted the SAE approach to fit total level models and to forecast economy variables as separate, independent variables in regression models. In addition, Seminole replaced data representative of the entire South Atlantic Census region with Member specific data. These data included Member residential appliance saturation survey statistics and commercial end-use intensity by industry weighted by service area employment.

Finally, in the 2017 load forecast study, Seminole developed incremental, additional behind-the-meter distributed solar generation forecasts for Members and their end-use consumers. Seminole incorporated this distributed solar generation forecast with the intent to reduce Seminole's expected energy and demand requirements in the future.

Exhibit No. __ (KDW-2) provides a detailed description of Seminole's current forecasting methodology and model/variable selection process.

Q. Does the analysis of forecasting error that Dr. Sotkiewicz presents on pages 14 through 16 of his testimony provide any useful information regarding the accuracy of Seminole's current load forecasting methodology?

A. No. Dr. Sotkiewicz analyzes the forecasts presented in Ten Year Site Plans from 2005 through 2013, none of which reflect Seminole's current load forecasting methodology. As I discussed previously, Seminole revised its methodology beginning in January 2015 (reflected in the 2016 Ten-Year Site Plan) and has continuously enhanced the forecast each year thereafter.

In addition, Dr. Sotkiewicz portrays Seminole's forecast error without historical context or comparison. Dr. Sotkiewicz begins calculating forecast errors in 2008 at the onset of the Great Recession. In fact, the majority of this analysis is associated with an unforeseen decline in the housing market and a weak economic recovery. As a point of comparison, many utilities across Florida struggled with load forecast errors during this period of time. Ultimately, it is not reasonable to assume the error in Seminole's 2017 forecast study will be similar to previous forecast errors associated with the effects of the Great Recession.

Q. Have you identified any other problems with Dr. Sotkiewicz's error analysis?

A. Yes. Dr. Sotkiewicz's error analysis does not fully account for the exit of Lee County Electric Cooperative (LCEC) from the Seminole-Member system, which began in 2010 and was complete in 2014. Seminole did not begin reflecting information of LCEC's exit until the 2008 Ten Year Site Plan (TYSP). Until that time, the forecasts reflected in Seminole's TYSP's included forecasts to serve LCEC's total requirements for the entire forecast period. Dr. Sotkiewicz failed to take this into account when he included the forecasts presented in the 2005, 2006 and 2007 TYSPs in his error analyses.

Second, Dr. Sotkiewicz incorrectly assumes that the load forecast studies produced in the TYSPs are generated in the same exact year, between January and March, before the TYSP is produced in April. Based on this incorrect assumption, Dr. Sotkiewicz begins counting "1 year out" 1-year after each TYSP is produced. However, Seminole's load forecast studies are generated a year in advance of being reported in the TYSP. As a result of this erroneous assumption, Dr. Sotkiewicz's analysis greatly overstates Seminole's historical forecast errors. These miscalculations are exacerbated in the 2005, 2006 and 2007 TYSPs because Seminole produced load forecast studies biannually before 2008. In other words, the 2005 TYSP reflects the 2003 load forecast study and the 2006 and 2007 TYSPs both reflect the 2005 load forecast study.

Q. Have you performed any analyses to provide a point of comparison to the error rates that Dr. Sotkiewicz presents for Seminole?

A. Yes. Putting aside the fundamental flaws with Dr. Sotkiewicz's analytical approach, I applied the same methodology that he utilized to calculate historical error rates for Duke Energy Florida (Duke) and Tampa Electric Company (TECO) over the same time period. These two utilities are both winter peaking, similar to Seminole. In addition, approximately 75% of

Seminole's Member loads are located in Duke's balancing area and much of Duke's service territory is geographically similar to Seminole's Members. In terms of relative size, TECO's consumer base and total load requirements are similar to Seminole.

Q. How do the error rates that you calculated for the other utilities compare to the error rates that Dr. Sotkiewicz presents for Seminole?

A. Although Dr. Sotkiewicz's error analysis is incorrect and overstates Seminole's forecast errors, we replicated his methodology for Duke and TECO's forecast errors to compare against Seminole. As shown in Exhibit No. __ (KDW-3), under Dr. Sotkiewicz's approach, the error rates for all three utilities are similar. For example, Winter Net Firm Demand forecast error "5 years out" based on Dr. Sotkiewicz's approach ranges from 39%-42% for Seminole, Duke and TECO. <u>I should emphasize that, in presenting these results, I do not mean to imply or suggest that Dr. Sotkiewicz's approach calculates the true forecast error for any of the three utilities</u>. I am simply providing the results for comparative purposes to show that the error analysis that he presented for Seminole does not support his suggestion that Seminole's forecasting error is "abysmal" relative to other utilities during the period in question.

Q. Have you performed an analysis to assess how the error rates presented in Dr. Sotkiewicz's testimony for Seminole would be affected if the flaws of Dr. Sotkiewicz's forecasts were corrected?

A. Yes. I first identified the load forecast study produced in each one of Seminole's TYSP since 2005. I then identified the forecast origin of each study, i.e. the last historical data point used to feed the forecast model, and counted each consecutive "year out" from the origin. For example, the forecast origin of the 2003 load forecast study is December 2002 and "1 year out" is the winter of 2003/2004. The table below shows each year out for Winter Net Firm Demand, Summer Net Firm Demand and Net Energy for Load, respectively.

2003 Load Forecast Study
2005 Ten Year Site Plan
<u>Winter Net Firm Demand</u>
Forecast Origin December 2002 (i.e. 2002/2003)
"1 Year Out" is 2003/2004
"2 Years Out" is 2004/2005
"3 Years Out" is 2005/2006
"4 Years Out" is 2006/2007
"5 Years Out" is 2007/2008
"6 Years Out" is 2008/2009 ("3 Years Out" in Sotkiewicz Analysis)
"7 Years Out" is 2010/2011 ("4 Years Out" in Sotkiewicz Analysis)
"8 Years Out" is 2011/2012 ("5 Years Out" in Sotkiewicz Analysis)

2003 Load Forecast Study
2005 Ten Year Site Plan
<u>Summer Net Firm Demand</u>
Forecast Origin December 2002
"1 Year Out" is 2004
"2 Years Out" is 2005
"3 Years Out" is 2006
"4 Years Out" is 2007
"5 Years Out" is 2008 ("3 Years Out" in Sotkiewicz Analysis)
"6 Years Out" is 2009 ("4 Years Out" in Sotkiewicz Analysis)
"7 Years Out" is 2010 ("5 Years Out" in Sotkiewicz Analysis)

2003 Load Forecast Study
2005 Ten Year Site Plan
<u>Net Energy for Load</u>
Forecast Origin is December 2002
"1 Year Out" is 2004
"2 Years Out" is 2005
"3 Years Out" is 2006
"4 Years Out" is 2007
"5 Years Out" is 2008 ("3 Years Out" in Sotkiewicz Analysis)

"6 Years Out" is 2009 ("4 Years Out" in Sotkiewicz Analysis)
"7 Years Out" is 2010 ("5 Years Out" in Sotkiewicz Analysis)

The approach that I utilized is consistent with the methodology used by the Commission to evaluate forecast error in at least one prior need determination proceeding in Order No. PSC-2016-0032-FOF-EI issued in Docket No. 20150196-EI.

Q. What were the results of your corrected error analysis?

A. As shown in Exhibit No. __ (KDW-4), when updated to reflect (1) actual forecast origin, (2) the exit of LCEC from the Seminole System, and (3) available data reflecting Seminole's recent Winter Net Firm Demand, the corrected version of Dr. Sotkiewicz's approach yields a historical forecast error of approximately 21%, which is approximately half of the 39% error rate presented in Dr. Sotkiewicz's testimony based on his flawed analysis. In presenting these results, I emphasize that this corrected version of Dr. Sotkiewicz's analysis based on studies conducted from 2003 through 2015 does not reasonably estimate forecast error associated with Seminole's current forecast, because as I discussed previously, Seminole's forecasting methodology has been improved since 2015. I simply present these results to show that Dr. Sotkiewicz's estimate of Seminole's historical forecast errors is overstated by more than 85%.

Q. Have you performed any analyses to evaluate Seminole's current forecasts since 2015?

A. Yes. Seminole has developed ex-post forecast error analyses on load forecast studies since 2015. Seminole's "after-the-event" evaluation of model error with observed (actual) explanatory variable data removes the error associated with long-term forecasts of weather and economy, providing valuable insight into model improvements. Seminole conducts this analysis with all available information one year after the forecast origin. In other words, we re-forecast the model with actual, observed data, rather than the forecast data. This provides an indication of whether load forecast error is due to Seminole's forecasting methodology or simply due to the fact that weather and economy forecasts are never perfect. Seminole conducts this analysis on a monthly resolution, which provides a higher temporal resolution than focusing on one individual observation such as the winter or summer peak, or annual energy.

Since 2015, Seminole has conducted ex-post analyses., Seminole calculates the error between actual load and ex-post load forecasts for each month and the Mean Absolute Percentage Error (MAPE) across all months. MAPE is a widely-used error measure in business forecasting, including load forecasting.

Q. What were the results of your ex post forecast analysis?

A. The monthly MAPE for the 2017 ex post analysis ranged from 2.3% to 3.5% in the demand model and 1.8% to 2.3% in the energy model. The results of the ex-post forecast analysis are shown in Exhibit No. __ (KDW-5).

Q. Does this conclude your testimony?

A. Yes.

Load Forecasting Whitepaper

Forecasting Methodology and Model/Variable Selection Process

Studies from 2015-2017

CONTENTS

Nomenclature of Terms

Abbreviation	Description
AEO	Annual Energy Outlook
BEA	U.S. Bureau of Economic Analysis
BEBR	University of Florida Bureau of Business and Economic Research
BLS	U.S. Bureau of Labor Statistics
BOC	U.S. Census Bureau
CDD	Cooling Degree Days
HDD	Heating Degree Days
EDR	Florida's Office of Economic and Demographic Research
EIA	U.S. Energy Information Administration
FORM-7	Member RUS Financial and Statistical Report
LFS	Load Forecast Study
MAPE	Mean Absolute Percentage Error
NEMS	National End-Use Modeling System
PBS	Power Billing System
RASS	Residential Appliance Saturation Survey
RUS	Rural Utilities Service
SAE	Statistically Adjusted End-use

Overview of Methodology: 2015 LFS – 2017 LFS

Seminole designs all models by Member and places emphasis on three models in particular:

1) Total Consumer Meters
2) Total Delivery Point Member Energy Purchases from Seminole
3) Total Delivery Point Member Non-Coincident Demand

In tandem with designing Member total level models for consumers and energy, Seminole designs models for each rate class—residential, commercial, and other. All rate class forecasts are reconciled bottom up to match total level forecasts.

Overview of Methodology: 2003 LFS – 2014 LFS

Prior to the 2015 LFS, the forecasting process was designed around four Member models:

1) Consumer Meters by Rate Class
2) Usage per Consumer by Rate Class Sales
3) Distribution Loss Factor
4) Delivery Point Load Factor

Member Energy Purchases from Seminole were a function of the first three models: consumers, usage per consumer and loss factor. Member non-coincident demands were a function of all four models: consumers, usage per consumer, loss factor and load factor.

Overview of Major Enhancements: 2015 LFS – 2017 LFS

Technology

In 2014, Seminole invested in state-of-the art statistical analysis software to move load forecasting data and models from “SAS® on the mainframe” to “SAS® on Windows PC.” The new technology enabled efficient data warehousing, coding, model design and analysis, and graphic visualization. Ultimately, this modern technology enabled Seminole to incorporate new data and engineer a robust forecasting process.

Weather Station Data

In 2014, Seminole more than tripled the number for weather stations it subscribes to from 8 previously, to 25, which cover a geographical area from the Everglades to southern Georgia. The types of weather variables collected from these stations increased substantially, as well. State-of-the-art weather station selection methodology was incorporated into the 2015 LFS to effectively choose which stations best represent weather in each Member territory.

The optimal set of weather stations by Member is derived by ranking the predictive power of each station's temperature readings to estimate electricity load and then re-estimating load based on combinatorial sets of stations ranked from lowest to highest MAPE. The set that achieves the lowest MAPE is chosen as the optimal combination. These analyses are conducted using regression models (PROC GLM in SAS®). The hourly weather profile of each Member is created by averaging the individual weather stations from a Member's optimal combination.

Economy Data

In the 2015 LFS, Seminole updated its approach to constructing economy variables for Member regression models. In previous forecasts, county-level data was weighted by the number of residential consumers in each Member service territory according to the most recent Member RASS. Member service areas are constantly changing; therefore modeling and forecasting load growth based on one set of weights provided limited flexibility. The updated approach does not weight, but aggregates in total the counties significant to Member service territories. The counties are deemed significant based on the following questions:

- What portion of a Member's consumers are from a given county?
- What portion of a given county's population is served by the Member?

The University of Florida Bureau of Business and Economic Research provides Seminole with annual updates to consumer by county distributions. Ultimately, this change in methodology resulted in minimal change to long-run forecasts.

In addition, Seminole no longer weights and combines economy projections from multiple sources and sparingly uses multiple third party sources for economy projections in a single regression model.

Load Data

A major focus area for improvement over previous LFS design was the use of monthly end-use sales data. Prior to the 2015 LFS, Seminole's methodology employed monthly-level, billing adjusted end-use meter data to forecast consumer meters and usage per meter by rate class. These forecasts were extrapolated along with loss factors and load factors to calculate Seminole's total energy and demand requirements at the delivery point, respectively. Since the 2015 LFS, hourly delivery point data has been used to model and forecasting total energy and demand requirements.

Energy Intensity Variables

Another focus area for improvement in the prior methodology was Seminole's use of appliance saturation data as a proxy for energy intensity trends in the usage per consumer model. Prior to 2015, Seminole treated the effects of energy efficient technologies in end-use regression models with space heating and cooling system saturation variables. These variables were derived from Members' RASS and publicly available manufacturing data.

During the development of the 2016 LFS, Seminole joined Itron's Energy Forecasting Group to enhance its ability to control for trends in structural changes, end-use appliance saturation, and efficiency. Itron provides residential and commercial SAE spreadsheets and models that are updated with the EIA's most recent results from the NEMS presented in the AEO. Data included in these spreadsheets by Census region include:

- Updated equipment efficiency trends
- Updated equipment and appliance saturation trends
- Updated structural indices
- Updated annual heating, cooling, water heating and Non-HVAC indices
- Updated regional sales forecasts

End-use saturation, efficiency, structural changes (building shell efficiency improvements and square footage), are combined with base year appliance usage to develop historical and projected end-use intensity estimates. These intensity values are used in constructing heating, cooling, and "other" usage variables for energy and demand forecasting models.

Seminole incorporated the SAE approach into its own methodology by making several improvements. First, for spatial precision, Seminole replaced Census region historical data and incorporated Member area statistics for residential appliance saturation and commercial end-use intensity weighted by employment by industry. Second, Seminole scaled all usage-per-consumer appliance intensity estimates in Itron's calibration process to a total-usage-per appliance level. Third, Seminole adjusted Itron's "HeatUse" and "CoolUse" components (shown in the equation below as "ThermalUse"), removed degree day weights (representing the effect of lag months), household size, household income, and electricity prices. Instead, Seminole models these factors as individual independent variables in statistical models to evaluate their statistical significance, as opposed to relying on the elasticities provided by Itron. In addition, the reasonableness of the forecast for each of these factors is critically reviewed before inclusion into regression models. Last, Seminole weights rate class thermal and base intensity estimates by rate class sales to derive total level intensities. The derivation of heating and cooling index variables (thermal variables) and base index variables for the residential model are shown below.

Residential SAE Model

$$\boldsymbol{XThermal_{y,m}} = \boldsymbol{ThermalIndex_{y}} * \boldsymbol{ThermalUse_{y,m}}$$

$$\boldsymbol{ThermalIndex_{y}} = StructuralIndex_{y} * \sum_{EquipmentType,i}^{EquipmentType,j} \left[Consumption_{EIA09} * \frac{Consumption_{Utility09}}{Consumption_{EIA09}} * \left(\frac{Saturation_{y} / Efficiency_{y}}{Saturation_{09} / Efficiency_{09}} \right) \right]$$

$$\boldsymbol{ThermalUse_{y,m}}\ (\textbf{SEMINOLE APPROACH}) = \frac{DD_{y,m}}{DD_{09}}$$

$$\boldsymbol{ThermalUse_{y,m}}\ (\textbf{ITRON APPROACH}) = \frac{WgtDD_{y,m}}{WgtDD_{09}} * \left(\frac{HHSize_{y}}{HHSize_{09}}\right)^{0.25} * \left(\frac{Income_{y}}{Income_{09}}\right)^{0.20} * \left(\frac{ElecPrice_{y}}{ElecPrice_{09}}\right)^{-0.15}$$

$$\boldsymbol{XBase_{y,m}} = BaseIndex_{y,m}$$

$$\boldsymbol{BaseIndex_{y,m}} = \sum_{Type,i}^{Type,j} \left[Consumption_{EIA09} * \frac{Consumption_{Utility09}}{Consumption_{EIA09}} * \left(\frac{Saturation_{y} / Efficiency_{y}}{Saturation_{09} / Efficiency_{09}} \right) * MthlyMultiplier_{y,m} \right]$$

Behind the Meter Distributed Solar

In the 2017 LFS, Seminole developed incremental, additional behind-the-meter distributed solar generation forecasts for Members and their end-use consumers. Seminole incorporated this distributed solar generation forecast with the intent to reduce Seminole's expected energy and demand requirements in the future. A detailed description of the data and model is presented later in this document.

Model Data: 2017 LFS

The availability of relevant data drives model development and variable selection. During LFS development, Seminole's staff updates and objectively analyzes all available data known to influence both consumer growth and electricity consumption. The load forecasting database is comprised of data from Seminole, its Members, and third party sources. All data is subject to validation tests and graphical analysis. Data cleansing techniques are employed when necessary.

Load and Consumer Data

Seminole collects load data for forecasting from two primary sources (1) Seminole System Operation's PBS and (2) Member FORM-7. Members provide their own forecast data for a select number of large commercial Members on Seminole economic development rates or interruptible rates. Members also provide scheduled load and customer transfers due to territorial agreements.

PBS contains hourly-interval delivery point meter data, which is useful for energy purchases and peak demand analysis. FORM-7's are provided by each of our nine Members to report electricity billing sales, revenue, and customers by rate class. FORM-7 sales show load consumption net of distribution line losses and include billing cycle adjustments that may not coincide with calendar-month consumption shown in PBS data.

Member FORM-7 data provides information about the number of customers, revenues and sales by rate class whereas PBS data does not contain this information. Rate class data typically requires more data cleansing than other sources and class level forecasts reconcile up to total level projections. A list of FORM-7 rate classifications by billing groups is shown below.

Member RUS FORM-7 Member Rate Classifications
Residential
Non-Seasonal
Seasonal
Pre-paid
Yard Light
Commercial
50 kVA or Less
Over 50 kVA
69 kVA or Over
1000 kVA or Less
Over 1000 kVA
General Service Demand
General Service Time of Day
General Service Less Than 50 kVA
Large General Service Demand
Contracted Rate
Large Power
Other Commercial
Public Buildings and Authorities
Interruptible

Other
Irrigation
Street and Highway Lighting
Public Buildings and Authorities
Sales for Re-sale

Economic and Demographic Data

Historical economic data employed in the LFS are produced by the BOC, the BEA, and the BLS. Seminole collects these data primarily from Moody's Analytics DataBuffet system. Forecasts of variables used in Seminole's forecasts are provided by Moody's, BEBR, and EDR. Moody's projects a range of economic variables at the county-level and re-forecasts these variables monthly. BEBR provides annual updates to Florida county population projections in five-year increments. EDR decomposes BEBR forecasts into yearly and quarterly increments and provides these data to the Florida Legislature to support policy making and planning decisions.

County population projections from Moody's Analytics and BEBR/EDR have traditionally been the primary resource for trending growth in the Seminole territory. Recent productions of the LFS have reflected trends based on BEBR population projections to a greater degree than in the past. BEBR's population forecasts have remained consistent over recent years, where Moody's forecasts are more aggressive than in prior vintages. Load forecasting models generally include only one source for trend variables, since economic variables from multiple-sources may not follow a logical conditional distribution. Seminole forecasts may reflect the combination of models with different data sources.

Proxies to population such as number of households and housing stock sometimes exhibit a higher degree of statistical efficiency when modeling residential consumers. The majority of consumers in the residential classification are dwellings and approximately 90 percent of the Seminole system is residential. Gross county product and total employment are useful alternatives for commercial models, since these variables exhibit more volatility during business cycles.

Energy Intensity Data

Seminole utilizes appliance energy consumption and equipment stock projections based on the EIA's NEMS to derive energy intensity indices in load forecast models. The EIA produces updates to total consumption and equipment stock by appliance type and by residential and commercial rate class in the AEO. Seminole retained Itron to access a clean and organized version of EIA's AOE's database for the South Atlantic Census region. Additionally, the RASS, updated every 5 years since 1980, captures historic rates in electric equipment stock growth. Census regional estimates of commercial square footage by building type are replaced with county-specific square footage estimates as a function of employment by industry from the BLS. A list of residential appliances used to generate energy intensity variables for forecast models are listed below by usage type.

Energy Efficiency Variables Residential Electrical Appliances and Equipment
Heating Use
Electric Furnace and Space Heating
Heat Pump Space Heating
Sectional Heating
Furnace Fans
Cooling Use
Central Air Conditioning and Room Air Conditioning
Central Air Conditioning Heat Pump Cooling
Base Use
Electric Water Heating
Electric Cooking
Primary and Secondary Refrigeration and Freezer
Dishwasher
Electric Clothes Washer
Electric Dryer
Television
Lighting
Miscellaneous

Seminole's load forecasting models include energy-efficiency variables for "heat-use", "cool-use", and "base-use" derived from Itron's SAE methodology. Itron provides Seminole both residential and commercial appliance saturation and efficiency data along with methodology for projecting end-use electricity consumption. Seminole scales Itron's usage-per-consumer variables to fit total-use models and derives parameter estimates for people per household, household income, and price independently in load models rather than indexing them together. Indices developed using saturation, efficiency and utilization data were interacted with CDD, HDD, and monthly dummy variables for use in energy and demand models. For seasonal demand models, seasonal CDD, HDD, minimum and maximum temperature terms are utilized.

Weather Station Data

Temperature variables used in in load forecasting models include average monthly temperature and minimum and maximum temperatures by month. Other temperature-related variables utilized in load forecasting models include HDD and CDD. HDD represent the sum of degrees each day's average temperature falls below 61° Fahrenheit in a given month, which is the approximate temperature consumers turn on heating devices. Alternatively, CDD represent the sum of degrees that each day's average temperature exceeds 72° Fahrenheit in a given month, which is the approximate temperature consumers turn on A/C units.

Weather variables used to forecast base-case future are based on “normal” weather. Normal weather in these forecasting models represent the 30-year median of historical monthly observations and average for season observations. Extreme weather used for alternative-scenario forecasts reflect the 10^{th} and 90^{th} percentiles.

Solar Data

Behind-the-meter solar installation and capacity records are collected from Customer-Owned Renewable Generation forms submitted by our individual Member cooperatives to the Florida Public Services Commission. Seminole also utilizes the end-use solar capacity forecasts published by the EIA in the AEO. Solar insolation data, which assume optimal conditions, are downloaded from an online calculator service operated by researchers at Arizona State University’s Solar Power Lab, after inputting the geo-coordinates of each of Seminole’s Member territories. AccuWeather provides Seminole with hourly weather data for a multitude of variables including temperature, solar irradiance, and minutes of sunshine for 25 selected stations in Florida and Georgia. Hourly solar insolation and AC power output data for Talquin’s 10 kW array were downloaded from their publicly viewable solar dashboard website for analysis purposes.

Load Forecasting Models: 2017 LFS

Seminole applies regression analysis to forecast number of consumers, energy, and demand. All models are developed at the Member-level, while and Seminole forecasts are the aggregate of Member-level forecasts. The different explanatory variables, combinations, transformations, and interactions capture the unique growth characteristics within the Members’ service territories. The summation of county-level data in each Member’s significant geographical area creates the explanatory variables unique to that Member’s territory. Regression models include lagged variables to control for autocorrelation as indicator variables to limit the bias associated with outliers that have not been removed during data cleansing. Additionally, indicator variables control for seasonality and isolate independent variables to certain months or seasons. Model selection focuses on minimizing MAPE. General study of current Member conditions and growth rates also aids in fitting models. The LFS reflects relevant Member-provided details regarding changes to the services territory and expected developments.

Consumer Model

Consumer forecasts are derived using regression analysis. In these models, the number of consumers is used as the dependent variable, while and population, number of households, and/or housing stock are used as independent variables. Historical data used in these models are from FORM-7 reports and U.S. BOC estimates. The training period extends over 40 years. Moody’s Analytics and BEBR provide the necessary data to project future number of consumers. Multiple models are fit to forecast per-Member total consumers and consumers by rate class. This hierarchical design allows for additional analysis of forecast errors and top-down reconciliation that mitigates disturbance caused by “rate-class shifts” in FORM-7 data. For additional model validation and analysis purposes consumer and population data by city/unincorporated area are collected from BEBR.

Seminole develops all consumer models with population as the trend variable and relies on projections produced by BEBR. Then, other economy variables are explored to improve consumer growth models. Other economy variables include housing stock and occupied households which are provided by Moody’s Analytics. If these alternative variables provide significant explanatory power throughout the training period, Seminole determines whether the future growth projections appear reasonable. Consumer growth forecasts using these alternative variables may be blended with BEBR population based forecasts. Seminole may also use population projections from Moody’s in the models that include Moody’s forecasts of housing stock or occupied households. Seminole also employs BEBR’s low population forecast for Members expecting minimal gains in consumer growth.

The third component of Seminole’s consumer model development process is analyzing which lags to include. Seminole utilizes autoregressive and moving average orders 1 and 12 to account for the correlation in consumer growth given consumer growth in prior periods. Seminole also analyzes how it can improve model accuracy through including binaries for seasonality and apparent errors in the data not accounted for in initial data cleaning. Finally, Seminole tests forecast model accuracy through an ex-post error analysis on the prior 12 months. Seminole may re-examine model specification and make changes based on holdout results.

Energy Model Overview

Forecasts of Member energy purchases from Seminole are developed using regression models. Seminole’s hourly power billing system, Member RUS FORM-7 financial reports, BOC estimates and AccuWeather make up the models historical data with model training periods of 20 years. Explanatory variables analyzed in these models include monthly temperature statistics interacted with energy efficiency indices, price, and economic indicators such as population, number of households, housing stock, and gross county product.

Rate-class energy retail sales to end-users, which are naturally lower than Member energy purchases at the delivery point by a loss factor, are grossed up to the energy purchases level and forecasted along with total purchases. The sum of rate class forecasts are reconciled to match total energy projections and reduced by projected losses to arrive at rate-class sales forecasts. Future expectations of the losses are projected off the five-year historical time trend between the ratio of annual Member retail sales to end-use consumers and Member purchases from Seminole.

Energy Model Development and Variable Selection Process

Seminole designs the energy forecasting models to include the following primary components:

- Member forecasted consumer growth or BEBR population projections
- Heating degree day, cooling degree day and base usage interacted with end-use appliance intensity forecasts provided by Itron
- Seminole's wholesale price to its Members in real terms.
- Precipitation
- Monthly binaries
- Autoregressive terms and moving average terms

Energy models for several members do not include base usage and price if the statistical significance is low or the parameter estimate's sign is counterintuitive. Seminole also tests specifications with relative humidity and heating and cooling degree days without energy intensity interactions. If these variables provide significant explanatory power to the model, they may be included, as well. Secondly, Seminole examines other variables that explain energy growth, including economic variables:

- Housing Stock
- Employment
- The natural log of gross product
- Household income in real terms

If these economic variables are effective in explaining energy growth, it is determined whether the growth projections for these variables provided by Moody's Analytics are reasonable and whether it is beneficial to incorporate these variables given knowledge of the service territory. The forecasts of energy growth using these alternative variables may be combined with or included in projections derived from BEBR population based models.
The third component of the energy model development is analyzing which time series components to include. For Seminole's smallest Member, an unobserved component model is incorporated to account for white noise and random walk due to a high level of commercial and industrial activity in training data. Finally, forecast model accuracy is analyzed through ex-post error analysis of the prior 12 months and model specification may revised based on these results.

Demand Model Overview

Demand for capacity forecasts are predictions of the most likely one-hour maximum peak in electricity consumption in a given month based off most probable economic and weather conditions at that point in time. Demand models are developed at the Member level and are trained with 20 years of training data. The different demand models make prediction for monthly demand, and for the winter and summer peaks. Demand model inputs include temperature statistics interacted with energy efficiency indices, economic trend variables, and load factor.

Peak models regress contemporaneous explanatory variables with the highest peak during December through March for Winter models and April through September for Summer models. Seasonal peak forecasts typically replace monthly-model results for the months seasonal peaks are most likely to occur.

Seminole's demand is the aggregate of the one-hour simultaneous demand of all Members that maximizes the peak of the system in a single month. The ratio between Member peak demand and Member demand coincident with the Seminole system as a whole derives the coincident factor. Member demands coincident with Seminole may be equal to or less than Member peak demand. Future expectations of Member coincident factors are extrapolated as the median of ten years of historical observations by month and by season.

Winter Demand Model Development and Variable Selection Process

Seminole develops the winter demand forecast model to include the following primary components:

- Member forecasted consumer growth or BEBR population projections
- Heating degree days and minimum temperature interacted with heating end-use equipment and appliance intensity forecasts provided by Itron
- Load Factor
- Seminole's Wholesale price to Members in real terms

Several Member models do not include price or minimum temperature variables if the statistical significance is low or if the parameter estimate's sign is counterintuitive. Seminole also attempts to use the base end-use intensity index to explain non-weather sensitive loads. However, the base-use parameter sometimes has low statistical significance in the winter demand model or a counterintuitive explanatory effect. In place of end-use base intensity, Seminole employs the natural logarithm or square root transformation on consumer-growth trend variables for nearly all Member models as a proxy for conservation growth. Seminole also examines other variables that explain demand growth, including:

- Average Relative Humidity
- Household income in real terms
- Maximum temperature interacted with end-use cooling equipment and appliance intensity forecasts provided by Itron

Finally, forecast model accuracy is analyzed through ex-post error analysis of the prior 12 months and model specification may revised based on these results.

Load Factor Model Development and Variable Selection Process

Load factor models are system-generated using SAS® Forecast Studio to produce the most efficient model using 20 years of observations and also for 12 and 48-month ex-post holdout periods. The final model based on results from this analysis. Trend variables are not employed in the load factor model or forecast. The variables used in the load factor model are shown below:

- Monthly maximum temperature
- Monthly minimum temperature
- Monthly average temperature
- Monthly mean humidity
- Monthly precipitation
- Temperature at time of Member peak
- Heating degree hours at the time of Member peak
- 3-hour moving average temperature leading up to Member peak
- 24-hour moving average heating degree hours leading up to Member peak
- 24-hour weighted moving average temperature leading up to Member peak
- 24-hour moving average temperature leading up to Member peak
- 48-hour moving average temperature leading up to Member peak
- 48-hour moving average cooling degree hours leading up to Member peak
- Number of days in the month
- Monthly binaries
- Monthly binaries interacted with weather statistics above

Alternative Models

Additional forecasts are prepared to manage the risks associated with inherent modeling error, changes in economic conditions, and weather uncertainty. Three sets of alternative projections provide upper and lower intervals around the baseline forecasts for consumers, energy, and demand. The first set of alternative projections are associated with the statistical error of each model at the 95 percent prediction interval. This interval shows the range into which approximately 95 percent of future projections will fall, if the distribution of forecast error is similar to the past distribution.

The second set of alternative scenarios are produced to show the projected outcome of severe and mild temperature events. These extreme weather cases cover the highest 90 percent and lowest 10 percent of historical temperature statistics in a Member's region. The last set of alternatives provide an upper and lower range into which future projections will fall, if the distribution of explanatory-variable forecast error is similar to the past distribution. BEBR provides a high and low interval around their "medium" population forecast. The BEBR high and low interval provides a rough approximation of error around explanatory variables employed in Seminole load forecasting models. Therefore, this alternative presents future outlooks of consumers, energy, and demand if the predictor variables deviate from their baseline trend.

Solar Model

Seminole developed projections of behind-the-meter solar output from future installations for each of its nine Members, and reduced energy and demand forecasts by these results. Outputs from existing behind-the-meter solar installations are reflected in actual energy and demand load history. Therefore the solar forecasts reflect only future increases in solar output. Existing generation is almost exclusively residential and forecasts are assumed to reflect residential-scale adoption. The forecast also includes an adjustment for a Member-owned 3.5 MW (AC) facility expected to come online during the summer of 2018.

The first component of the solar forecasts includes Member-level projections of total annual AC capacity growth. Linear and exponential models were trained with a five-year trend in capacity growth. These data are contained in net metering reports submitted by Members to the PSC and are publically available online. These capacity forecasts were presented individually to Members and reflect edits from feedback received during each consultation. Long-term growth in this analysis was extrapolated at a monthly level from national end-use solar projections published in the EIA's AEO.

Using historic weather data from the unique station-combination created for each member, normalized statistics for minutes-of-sunshine by hour were combined with optimal-condition solar insolation data to create hourly solar potential profiles for each Member territory. These profiles reflect not just the quality of sunlight typical for each territory throughout the year, but also the quantity of this sunlight typically available during each hour of a normal year.

The final component of the solar forecasting model combines the hourly solar-potential index curve with the projected monthly solar installations to create hourly solar generation forecasts. Results from this engineering approach were then calibrated using observed hourly radiance and solar generation data collected from sensors integrated into Talquin's 10 kW array. These data are publicly available on their solar dashboard website. Total energy projections are reduced by monthly aggregates of forecasted solar generation, and demand forecasts are reduced by solar output at the time of peak demand. For LFS winter/summer peak demand forecasts, unique solar potential index curves were derived for winter and summer, respectively. These unique curves incorporate ten years of actual winter-peak hour and summer-peak hour data to calculate the average number of minutes of sunshine, during each respective peak event.

LFS Vintage Factsheet

2013 LFS
Prepared by: Bill Lawton, Kyle Wood, Sarah Bridges and Gerardo Lopez
Primary Models: End-Use Consumers, End-Use Sales, Loss Factor, Load Factor
Primary Source for Load Data: Member Monthly End-Use Billing Report by Rate Class
Weather Stations: 8
Weather Normalization: 25 Years
Statistical Software: Mainframe SAS®
Forecast Origin: December 2012
Presented in TYSP: 2014

2014 LFS
Prepared by: Bill Lawton, Kyle Wood, Sarah Bridges and Gerardo Lopez
Primary Models: End-Use Consumers, End-Use Sales, Loss Factor, Load Factor
Primary Source for Load Data: Member Monthly End-Use Billing Report by Rate Class
Weather Stations: 8
Weather Normalization: 25 Years
Statistical Software: Mainframe SAS®
Forecast Origin: December 2013
Presented in TYSP: 2015

2015 LFS
Prepared by Kyle Wood and Gerardo Lopez
Primary Models: End-Use Consumers, Total Energy Purchases, Load Factor, Total Demand
Primary Source for Load Data: Seminole Hourly Delivery Point Meter
Weather Stations: 25
Weather Normalization: 30 Years
Statistical Software: SAS® on Windows PC (DI Studio, Enterprise Guide, Forecast Studio)
Forecast Origin: December 2014Major Enhancement: State-of-the-art Weather Station Selection Process
Forecast Origin: December 2014
Presented in TYSP: 2016

2016 LFS
Prepared by: Kyle Wood and Matthew Siler
Primary Models: End-Use Consumers, Total Energy Purchases, Load Factor, Total Demand
Primary Source for Load Data: Seminole Hourly Delivery Point Meter
Weather Stations: 25
Weather Normalization: 30 Years
Statistical Software: SAS® on Windows PC (DI Studio, Enterprise Guide, Forecast Studio)
Forecast Origin: February 2016
Major Enhancement: Residential and Commercial End-Use Intensity Variables
Forecast Origin: February 2016
Presented in TYSP: 2017

2017 LFS
Prepared by: Kyle Wood, Matthew Siler, Abby Mayer
Primary Models: End-Use Consumers, Total Energy Purchases, Load Factor, Total Demand
Primary Source for Load Data: Seminole Hourly Delivery Point Meter
Weather Stations: 25
Weather Normalization: 30 Years
Statistical Software: SAS® on Windows PC (DI Studio, Enterprise Guide, Forecast Studio)
Forecast Origin: February 2017
Major Enhancement: Behind the Meter Distributed Solar Forecast
Forecast Origin: February 2017
Presented in TYSP: 2018

Latest LFS Initiatives

Seminole upgraded the primary software platform to SAS® Windows version M.4 Maintenance Release 4 in June of 2017. The latest upgrade provides Seminole access to the state of the art applications, including SAS® Energy Forecasting and SAS® Visual Analytics. The Energy Forecasting application will provide Seminole additional capability to develop and implement probabilistic forecasting methodology. Seminole will also have enhanced capability to view data for analysis and reporting through SAS® Visual Analytics.

SEMINOLE ELECTRIC COPPERATIVE, INC
WINTER NET FIRM DEMAND (MW)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference				% Difference		
Year	5 Years Out	4 Years Out	3 Years Out	Year	5 Years Out	4 Years Out	3 Years Out
2005				2005			
2006				2006			
2007				2007			
2008			125	2008			2.64%
2009		21	166	2009		0.42%	3.29%
2010	970	1,099	1,092	2010	22.48%	25.47%	25.31%
2011	1,699	1,692	1,161	2011	43.36%	43.19%	29.63%
2012	2,113	1,586	1,096	2012	57.00%	42.78%	29.57%
2013	1,344	1,069	992	2013	41.48%	32.99%	30.62%
2014	853	758	698	2014	23.74%	21.10%	19.43%
2015	1,174	1,099	885	2015	35.50%	33.23%	26.76%
2016	1,511	1,308	1,128	2016	50.07%	43.34%	37.38%
AVERAGE	**1,381**	**1,079**	**816**	**AVERAGE**	**39.09%**	**30.31%**	**22.73%**

Season	Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005-06	2005										
2006-07	2006										
2007-08	2007										
2008-09	2008	4,738	4,863								
2009-10	2009	5,047	5,068	5,213							
2010-11	2010	4,315	5,285	5,414	5,407						
2011-12	2011	3,918		5,617	5,610	5,079					
2012-13	2012	3,707			5,820	5,293	4,803				
2013-14	2013	3,240				4,584	4,309	4,232			
2014-15	2014	3,593					4,446	4,351	4,291		
2015-16	2015	3,307						4,481	4,406	4,192	
2016-17	2016	3,018							4,529	4,326	4,146

DUKE ENERGY FLORIDA
WINTER NET FIRM DEMAND (MW)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			99
2009		(1,157)	(1,146)
2010	1,454	1,440	1,397
2011	3,274	3,293	3,273
2012	4,387	4,357	3,835
2013	4,096	3,391	2,398
2014	2,528	1,385	1,508
2015	2,360	2,538	2,375
2016	NA	NA	NA
AVERAGE	**3,017**	**2,178**	**1,717**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			0.99%
2009		-9.91%	-9.82%
2010	15.65%	15.50%	15.04%
2011	42.51%	42.76%	42.50%
2012	63.64%	63.21%	55.64%
2013	56.72%	46.95%	33.20%
2014	30.43%	16.67%	18.15%
2015	31.95%	34.36%	32.16%
2016	NA	NA	NA
AVERAGE	**40.15%**	**29.94%**	**23.48%**

Season	Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005-06	2005										
2006-07	2006										
2007-08	2007										
2008-09	2008	10,034	10,133								
2009-10	2009	11,670	10,513	10,524							
2010-11	2010	9,288	10,742	10,728	10,685						
2011-12	2011	7,701		10,975	10,994	10,974					
2012-13	2012	6,893			11,280	11,250	10,728				
2013-14	2013	7,222				11,318	10,613	9,620			
2014-15	2014	8,308					10,836	9,693	9,816		
2015-16	2015	7,386						9,746	9,924	9,761	
2016-17	2016	NA							9,889	9,682	9,910

TAMPA ELECTRIC COMPANY
WINTER NET FIRM DEMAND (MW)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			565
2009		209	157
2010	882	809	833
2011	1,412	1,433	1,343
2012	1,921	1,824	1,427
2013	1,797	1,360	916
2014	1,146	654	642
2015	925	916	784
2016	NA	NA	NA
AVERAGE	**1,347**	**1,029**	**833**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			15.05%
2009		4.91%	3.69%
2010	23.61%	21.66%	22.30%
2011	43.22%	43.86%	41.11%
2012	65.83%	62.51%	48.90%
2013	58.36%	44.17%	29.75%
2014	33.81%	19.29%	18.94%
2015	29.17%	28.89%	24.72%
2016	NA	NA	NA
AVERAGE	**42.33%**	**32.18%**	**25.56%**

Season	Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005-06	2005										
2006-07	2006										
2007-08	2007										
2008-09	2008	3,754	4,319								
2009-10	2009	4,256	4,465	4,413							
2010-11	2010	3,735	4,617	4,544	4,568						
2011-12	2011	3,267		4,679	4,700	4,610					
2012-13	2012	2,918			4,839	4,742	4,345				
2013-14	2013	3,079				4,876	4,439	3,995			
2014-15	2014	3,390					4,536	4,044	4,032		
2015-16	2015	3,171						4,096	4,087	3,955	
2016-17	2016	NA							4,145	4,003	3,887

SEMINOLE ELECTRIC COPPERATIVE, INC
SUMMER NET FIRM DEMAND (MW)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			112
2009		71	176
2010	508	609	604
2011	652	646	378
2012	1,026	769	645
2013	799	704	582
2014	631	549	412
2015	713	557	329
2016	439	218	69
AVERAGE	**681**	**515**	**367**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			3.09%
2009		1.86%	4.60%
2010	14.32%	17.16%	17.02%
2011	17.85%	17.68%	10.35%
2012	29.93%	22.43%	18.82%
2013	22.41%	19.74%	16.32%
2014	20.43%	17.78%	13.34%
2015	23.60%	18.44%	10.89%
2016	13.54%	6.72%	2.13%
AVERAGE	**20.30%**	**15.23%**	**10.73%**

Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005										
2006										
2007										
2008	3,630	3,742								
2009	3,824	3,895	4,000							
2010	3,548	4,056	4,157	4,152						
2011	3,653		4,305	4,299	4,031					
2012	3,428			4,454	4,197	4,073				
2013	3,566				4,365	4,270	4,148			
2014	3,088					3,719	3,637	3,500		
2015	3,021						3,734	3,578	3,350	
2016	3,243							3,682	3,461	3,312

DUKE ENERGY FLORIDA
SUMMER NET FIRM DEMAND (MW)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			1
2009		(271)	(71)
2010	790	1,002	872
2011	1,518	1,356	1,237
2012	1,836	1,858	1,548
2013	2,376	2,058	1,109
2014	1,540	464	360
2015	621	495	533
2016	(180)	(36)	427
AVERAGE	**1,214**	**866**	**668**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			0.01%
2009		-2.82%	-0.74%
2010	8.85%	11.22%	9.77%
2011	17.58%	15.70%	14.32%
2012	22.02%	22.29%	18.57%
2013	29.64%	25.67%	13.83%
2014	18.07%	5.44%	4.22%
2015	7.37%	5.87%	6.32%
2016	-2.00%	-0.40%	4.74%
AVERAGE	**14.50%**	**10.37%**	**7.89%**

Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005										
2006										
2007										
2008	9,185	9,186								
2009	9,624	9,353	9,553							
2010	8,929	9,719	9,931	9,801						
2011	8,636		10,154	9,992	9,873					
2012	8,337			10,173	10,195	9,885				
2013	8,017				10,393	10,075	9,126			
2014	8,523					10,063	8,987	8,883		
2015	8,431						9,052	8,926	8,964	
2016	9,014							8,834	8,978	9,441

TAMPA ELECTRIC COMPANY
SUMMER NET FIRM DEMAND (MW)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			250
2009		308	292
2010	534	504	525
2011	639	658	592
2012	857	788	556
2013	925	657	290
2014	605	199	107
2015	220	125	75
2016	52	(7)	(119)
AVERAGE	**547**	**404**	**285**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			6.72%
2009		8.11%	7.69%
2010	14.39%	13.58%	14.15%
2011	17.27%	17.79%	16.00%
2012	23.63%	21.73%	15.33%
2013	25.59%	18.18%	8.02%
2014	16.10%	5.30%	2.85%
2015	5.81%	3.30%	1.98%
2016	1.33%	-0.18%	-3.05%
AVERAGE	**14.88%**	**10.98%**	**7.74%**

Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005										
2006										
2007										
2008	3,723	3,973								
2009	3,799	4,107	4,091							
2010	3,710	4,244	4,214	4,235						
2011	3,699		4,338	4,357	4,291					
2012	3,627			4,484	4,415	4,183				
2013	3,614				4,539	4,271	3,904			
2014	3,757					4,362	3,956	3,864		
2015	3,784						4,004	3,909	3,859	
2016	3,907							3,959	3,900	3,788

SEMINOLE ELECTRIC COPPERATIVE, INC
NET ENERGY FOR LOAD (GWh)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			1,028
2009		1,674	2,248
2010	2,614	3,168	3,123
2011	5,254	5,208	3,065
2012	6,338	4,150	2,787
2013	4,932	3,528	2,859
2014	3,024	2,358	1,974
2015	2,552	2,108	1,286
2016	2,222	1,435	963
AVERAGE	**3,848**	**2,954**	**2,148**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			5.93%
2009		9.59%	12.88%
2010	15.07%	18.26%	18.00%
2011	32.76%	32.47%	19.11%
2012	40.19%	26.32%	17.67%
2013	31.19%	22.31%	18.08%
2014	21.83%	17.02%	14.25%
2015	18.09%	14.95%	9.12%
2016	15.35%	9.92%	6.65%
AVERAGE	**24.93%**	**18.86%**	**13.52%**

Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005										
2006										
2007										
2008	17,332	18,360								
2009	17,453	19,127	19,701							
2010	17,346	19,960	20,514	20,469						
2011	16,037		21,291	21,245	19,102					
2012	15,769			22,107	19,919	18,556				
2013	15,812				20,744	19,340	18,671			
2014	13,854					16,878	16,212	15,828		
2015	14,104						16,656	16,212	15,390	
2016	14,471							16,693	15,906	15,434

DUKE ENERGY FLORIDA
NET ENERGY FOR LOAD (GWh)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			2,909
2009		7,524	6,024
2010	7,381	5,846	6,356
2011	10,729	11,286	10,423
2012	13,803	13,481	11,271
2013	15,273	12,875	5,105
2014	11,784	5,483	5,392
2015	4,535	4,514	1,353
2016	3,322	742	567
AVERAGE	**9,547**	**7,719**	**5,489**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			6.10%
2009		17.05%	13.65%
2010	15.99%	12.66%	13.77%
2011	25.25%	26.56%	24.53%
2012	33.49%	32.71%	27.35%
2013	37.46%	31.58%	12.52%
2014	28.76%	13.38%	13.16%
2015	10.73%	10.68%	3.20%
2016	7.75%	1.73%	1.32%
AVERAGE	**22.78%**	**18.29%**	**12.85%**

Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005										
2006										
2007										
2008	47,658	50,567								
2009	44,124	51,648	50,148							
2010	46,160	53,541	52,006	52,516						
2011	42,490		53,219	53,776	52,913					
2012	41,214			55,017	54,695	52,485				
2013	40,772				56,045	53,647	45,877			
2014	40,975					52,759	46,458	46,367		
2015	42,280						46,815	46,794	43,633	
2016	42,854							46,176	43,596	43,421

TAMPA ELECTRIC COMPANY
NET ENERGY FOR LOAD (GWh)
Comparison of Historical Error Rates based on Sotkiewicz Approach

	Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			1,750
2009		3,147	3,302
2010	2,904	2,986	2,778
2011	4,744	4,437	4,014
2012	4,990	4,553	3,251
2013	5,228	3,792	2,107
2014	4,067	2,155	1,244
2015	1,624	661	253
2016	834	398	(382)
AVERAGE	**3,484**	**2,766**	**2,035**

	% Difference		
Year	5 Years Out	4 Years Out	3 Years Out
2005			
2006			
2007			
2008			8.47%
2009		15.78%	16.56%
2010	14.05%	14.45%	13.44%
2011	24.58%	22.99%	20.80%
2012	25.83%	23.57%	16.83%
2013	27.26%	19.77%	10.99%
2014	21.06%	11.16%	6.44%
2015	8.08%	3.29%	1.26%
2016	4.13%	1.97%	-1.89%
AVERAGE	**17.86%**	**14.12%**	**10.32%**

Year	Actual	TYSP2005	TYSP2006	TYSP2007	TYSP2008	TYSP2009	TYSP2010	TYSP2011	TYSP2012	TYSP2013
2005										
2006										
2007										
2008	20,650	22,400								
2009	19,943	23,090	23,245							
2010	20,667	23,571	23,653	23,445						
2011	19,298		24,042	23,735	23,312					
2012	19,320			24,310	23,873	22,571				
2013	19,177				24,405	22,969	21,284			
2014	19,315					23,382	21,470	20,559		
2015	20,105						21,729	20,766	20,358	
2016	20,173							21,007	20,571	19,791

Winter Net Firm Demand (MW)
Historical Seminole Error Rates based on Corrected Sotkiewicz Approach
Load Forecast Studies 2003 through 2015
Adjusted for Lee County Electric Cooperative, Inc.

	LFS	Forecast Origin	TYSP	(FORECAST - ACTUAL) 3 Years Out	4 Years Out	5 Years Out	(FORECAST - ACTUAL) / ACTUAL 3 Years Out	4 Years Out	5 Years Out
	2003 LFS	Dec.2002	2005 TYSP	79	457	348	1.87%	11.35%	8.24%
	2005 LFS	Dec.2004	2006 TYSP	581	266	-139	13.76%	5.61%	-2.75%
*	2005 LFS	Dec.2004	2007 TYSP	575	259	-146	13.62%	5.47%	-2.89%
	2007 LFS	Dec.2006	2008 TYSP	-388	552	1,161	-7.69%	12.79%	29.63%
	2008 LFS	Dec.2007	2009 TYSP	192	731	1,096	4.45%	18.66%	29.57%
	2009 LFS	Dec.2008	2010 TYSP	688	1,049	992	17.56%	28.30%	30.62%
	2010 LFS	Dec.2009	2011 TYSP	1,047	951	698	28.24%	29.35%	19.43%
	2011 LFS	Dec.2010	2012 TYSP	693	461	885	21.39%	12.83%	26.76%
	2012 LFS	Dec.2011	2013 TYSP	356	715	1,128	9.91%	21.62%	37.38%
	2013 LFS	Dec.2012	2014 TYSP	559	960	238	16.90%	31.81%	6.18%
	2014 LFS	Dec.2013	2015 TYSP	498	-265		16.50%	-6.88%	
	2015 LFS	Dec.2014	2016 TYSP	-314			-8.15%		
			AVERAGE	**381**	**558**	**626**	**10.70%**	**15.54%**	**18.22%**
			AVERAGE *(Excluding Duplicate)	**363**	**588**	**712**	**10.43%**	**16.54%**	**20.56%**

Note: Load Forecast Study Conducted Bi-Annually prior to 2008.
Source: Ten Year Site Plans 2005 through 2016.

Summer Net Firm Demand (MW)
Historical Seminole Error Rates based on Corrected Sotkiewicz Approach
Load Forecast Studies 2003 through 2014
Adjusted for Lee County Electric Cooperative, Inc.

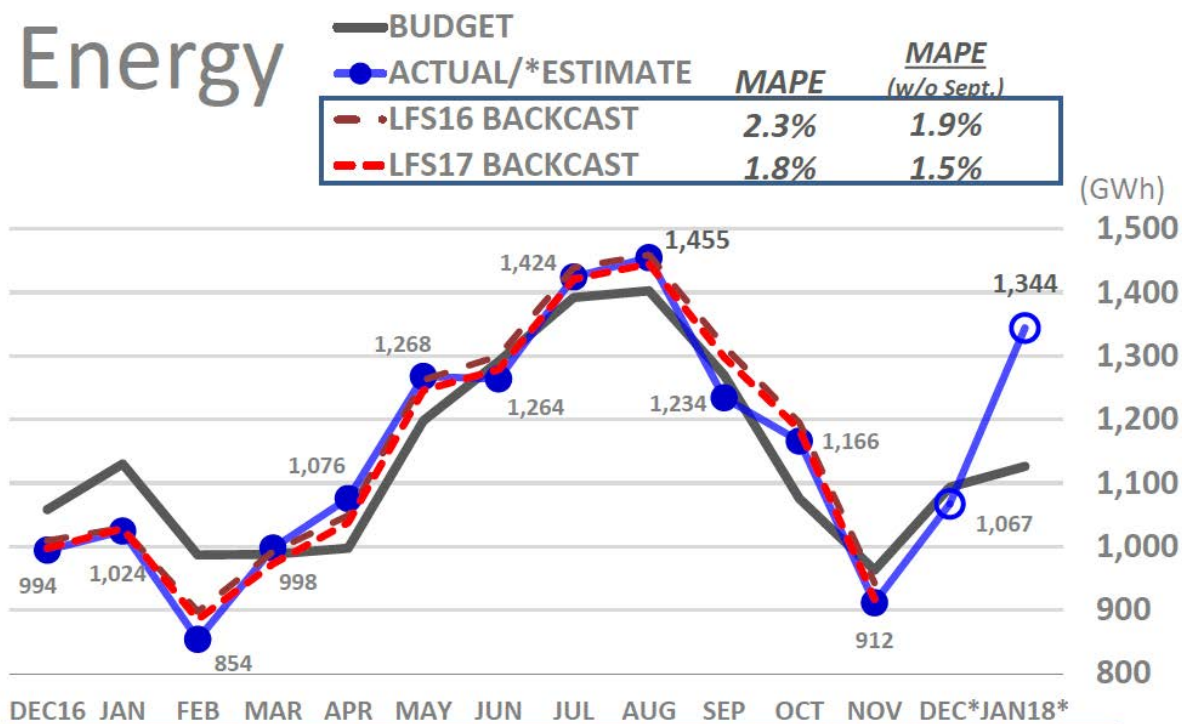
	LFS	Forecast Origin	TYSP	(FORECAST - ACTUAL)			(FORECAST - ACTUAL) / ACTUAL		
				3 Years Out	*4 Years Out*	*5 Years Out*	*3 Years Out*	*4 Years Out*	*5 Years Out*
	2003 LFS	Dec.2002	2005 TYSP	-172	-241	112	-4.74%	-6.28%	3.09%
	2005 LFS	Dec.2004	2006 TYSP	216	176	382	5.95%	4.60%	10.77%
*	2005 LFS	Dec.2004	2007 TYSP	211	171	377	5.81%	4.47%	10.63%
	2007 LFS	Dec.2006	2008 TYSP	314	378	769	8.85%	10.35%	22.43%
	2008 LFS	Dec.2007	2009 TYSP	293	645	704	8.02%	18.82%	19.74%
	2009 LFS	Dec.2008	2010 TYSP	590	582	549	17.21%	16.32%	17.78%
	2010 LFS	Dec.2009	2011 TYSP	463	412	557	12.98%	13.34%	18.44%
	2011 LFS	Dec.2010	2012 TYSP	164	329	218	5.31%	10.89%	6.72%
	2012 LFS	Dec.2011	2013 TYSP	254	69	288	8.41%	2.13%	9.25%
	2013 LFS	Dec.2012	2014 TYSP	-43	177		-1.33%	5.68%	
	2014 LFS	Dec.2013	2015 TYSP	-92			-2.95%		
			AVERAGE	**200**	**270**	**440**	**5.78%**	**8.03%**	**13.20%**
			AVERAGE *(Excluding Duplicate)	**199**	**281**	**447**	**5.77%**	**8.43%**	**13.53%**

Note: Load Forecast Study Conducted Bi-Annually prior to 2008.
Source: Ten Year Site Plans 2005 through 2015.

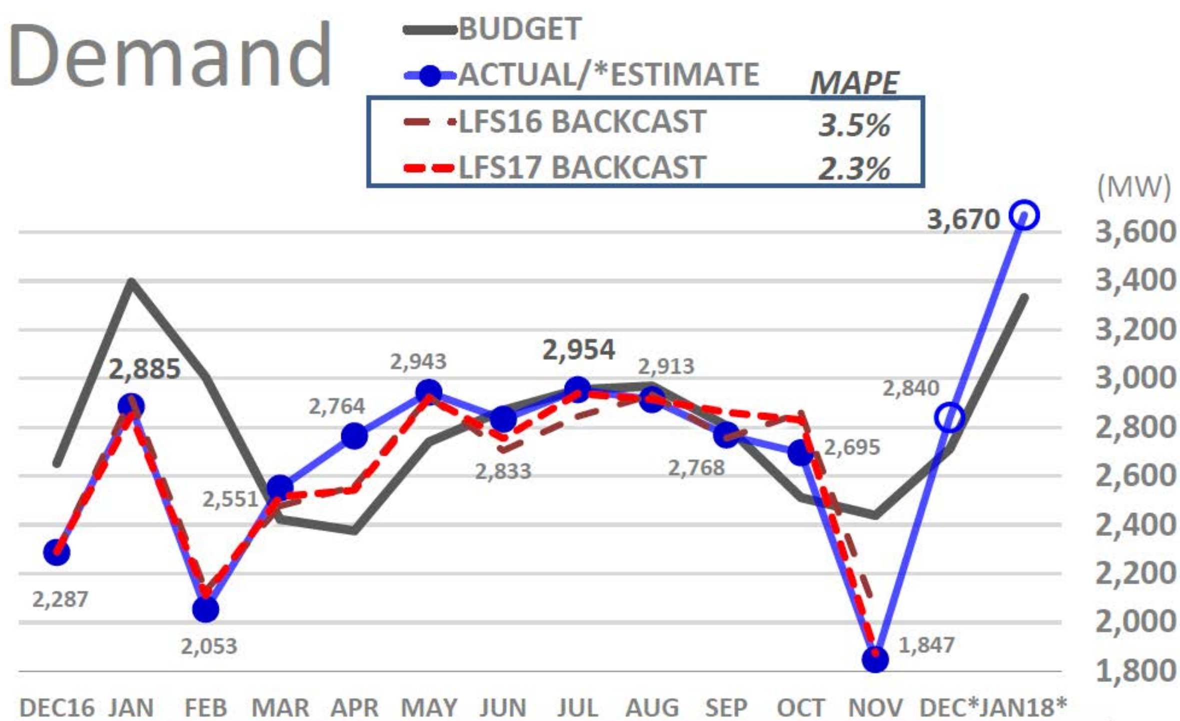
Net Energy for Load (GWh)
Historical Seminole Error Rates based on Corrected Sotkiewicz Approach
Load Forecast Studies 2003 through 2014
Adjusted for Lee County Electric Cooperative, Inc.

			(FORECAST - ACTUAL)			(FORECAST - ACTUAL) / ACTUAL		
LFS	Forecast Origin	TYSP	*3 Years Out*	*4 Years Out*	*5 Years Out*	*3 Years Out*	*4 Years Out*	*5 Years Out*
2003 LFS	Dec.2002	2005 TYSP	-365	-97	1,028	-2.12%	-0.55%	5.93%
2005 LFS	Dec.2004	2006 TYSP	1,625	2,248	1,869	9.38%	12.88%	10.77%
* 2005 LFS	Dec.2004	2007 TYSP	1,584	2,205	1,824	9.14%	12.63%	10.52%
2007 LFS	Dec.2006	2008 TYSP	933	3,065	4,150	5.38%	19.11%	26.32%
2008 LFS	Dec.2007	2009 TYSP	1,945	2,787	3,528	12.13%	17.67%	22.31%
2009 LFS	Dec.2008	2010 TYSP	2,331	2,859	2,358	14.78%	18.08%	17.02%
2010 LFS	Dec.2009	2011 TYSP	2,678	1,974	2,108	16.94%	14.25%	14.95%
2011 LFS	Dec.2010	2012 TYSP	1,066	1,286	1,435	7.69%	9.12%	9.92%
2012 LFS	Dec.2011	2013 TYSP	952	963	1,557	6.75%	6.65%	10.87%
2013 LFS	Dec.2012	2014 TYSP	823	1,414		5.69%	9.87%	
2014 LFS	Dec.2013	2015 TYSP	-57			-0.40%		
		AVERAGE	**1,229**	**1,870**	**2,206**	**7.76%**	**11.97%**	**14.29%**
		AVERAGE *(Excluding Duplicate)	**1,193**	**1,833**	**2,254**	**7.62%**	**11.90%**	**14.76%**

Note: Load Forecast Study Conducted Bi-Annually prior to 2008.
Source: Ten Year Site Plans 2005 through 2015.



-1.5%	-0.5%	-5.1%	0.6%	2.5%	0.4%	-2.9%	-1.0%	-0.3%	-6.6%	-2.5%	-3.4%	LFS16 Backcast
-0.3%	-0.4%	-3.7%	2.5%	3.5%	1.7%	-1.2%	0.2%	0.7%	-5.2%	-1.6%	-0.6%	LFS17 Backcast



-0.1%	-1.2%	-3.7%	2.9%	7.5%	0.6%	4.5%	3.7%	-0.7%	0.5%	-6.1%	-10.9%	LFS16 Backcast
-0.1%	1.3%	-2.8%	1.4%	8.1%	0.8%	2.8%	0.5%	0.0%	-3.4%	-5.0%	-1.5%	LFS17 Backcast

*December 2017 and January 201 are Estimated-Actual
Note: **In Sample Fit** through February 2017.

BEFORE THE FLORIDA PUBLIC SERVICE COMMISSION

DOCKET NOS. 20170266-EC and 20170267-EC

IN RE: PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., FOR DETERMINATION OF NEED FOR SEMINOLE COMBINED CYCLE FACILITY

IN RE: JOINT PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., AND SHADY HILLS ENERGY CENTER, LLC., FOR DETERMINATION OF NEED FOR SHADY HILLS COMBINED CYCLE FACILITY

REBUTTAL TESTIMONY OF:

TAO HONG, PH.D.

BEFORE THE PUBLIC SERVICE COMMISSION

SEMINOLE ELECTRIC COOPERATIVE

REBUTTAL TESTIMONY OF

TAO HONG, PH.D.

DOCKET NOS. 20170266 and 20170267-EC

FEBRUARY 19, 2018

Q. Please state your name and address.

A. My name is Tao Hong. My address is 1507 Willow Oak Pond Ln, Charlotte, NC 28270.

Q. By whom are you employed and in what capacity?

A. I am employed by the University of North Carolina at Charlotte ("UNC Charlotte") as Associate Professor and Research Director of Systems Engineering and Engineering Management Department, Director of BigDEAL (Big Data Energy Analytics Laboratory), NCEMC Faculty Fellow of Energy Analytics, and associate of the Energy Production and Infrastructure Center. I am Owner and Chief Data Scientist of Hong Analytics, LLC, which is a private consulting firm that I founded in 2015.

Q. What are your responsibilities in your positions with UNC Charlotte?

A. I teach undergraduate and graduate level courses offered by the Systems Engineering and Engineering Management Department. I conduct research mostly in the area of load forecasting. I provide professional services within and outside the university.

Q. What services do you provide through Hong Analytics, LLC?

A. I provide training and consulting services to industry organizations. My primary practice area is load forecasting. I have served more than 100 organizations worldwide. Most of them are energy companies.

Q. Have you worked with Seminole Electric Cooperative, Inc., ("Seminole") prior to your involvement in this case?

A. Yes. I helped Seminole set up a short term load forecasting system in 2017.

Q. Please describe your professional experience prior to joining UNC Charlotte?

A. Prior to joining UNC Charlotte, I was a Senior Industry Consultant at SAS Institute Inc., where I led research, development, consulting, marketing and sales of the forecasting vertical of the energy business unit. I was a Principal Engineer at Quanta Technology, where I led forecasting related consulting projects and tasks. I was an adjunct instructor at North Carolina State University, teaching load forecasting and demand response related topics at both Electrical & Computer Engineering Department and the Institute for Advanced Analytics.

Q. Please describe your educational background.

A. I received a Bachelor of Engineering degree in Automation from Tsinghua University in Beijing, an M.S. degree in Electrical Engineering, an M.S. degree with co-majors in Industrial Engineering and Operations Research, and a Ph.D. degree with co-majors in Operations Research and Electrical Engineering from

North Carolina State University. My master thesis was on long term spatial load forecasting. My doctoral dissertation was on short term electric load forecasting.

Q. What are your major areas of expertise?

A. My major areas of expertise are in forecasting and optimization. I have applied various statistical and optimization techniques to the development of algorithms and tools for utility applications of analytics. Most of my work is in the area of energy forecasting.

Q. Please describe any memberships or leadership roles you hold in any professional organizations.

A. I am the Founding Chair of the IEEE (Institute of Electrical and Electronics Engineers) Working Group on Energy Forecasting. I am a Director at Large of the International Institute of Forecasters. I am the General Chair of Global Energy Forecasting Competitions. In addition, I am an editor of IEEE Transactions on Smart Grid, associate editor of International Journal of Forecasting and Journal of Modern Power Systems and Clean Energy, and editorial board member of IEEE Power and Energy Magazine.

Q. Do you teach outside of your position at UNC Charlotte?

Yes. I currently teach five courses outside UNC Charlotte: "Fundamentals of Utility Analytics: Techniques, Applications and Case Studies;" "Introduction to Energy Forecasting;" "Electric Load Forecasting: Fundamentals and Best Practices;" "Long Term Load Forecasting;" and "Electric Load Forecasting:

Advanced Topics and Case Studies." Hundreds of working professionals from more than a dozen countries have taken these courses.

Q. What, if any, peer-reviewed articles and professional reports have you published.

A. As of February 2018, I have published more than 40 papers, including 21 scholarly journal papers, 15 conference papers, 6 magazine articles, and a 171-page report "Load Forecasting Case Study" commissioned by the Eastern Interconnection States' Planning Council and sponsored by National Association of Regulatory Utility Commissioners. According to Google Scholar, my papers have been cited more than 1,000 times since 2013. My curriculum vitae, which is attached as Exhibit No. __ (TAO-1), includes a listing of all my publications.

Q. Have you won any awards in your field?

A. Yes. I have won the following awards in the recent five years:

- Charlotte Business Journal Energy Education Leader of the Year (2017)
- IEEE PES Power Systems Planning and Implementation Technical Committee Prize Paper Award (2016, for the paper "Long Term Probabilistic Load Forecasting and Normalization With Hourly Information" published by IEEE Transactions on Smart Grid)
- IEEE PES PSPI Technical Committee Working Group Recognition Award (2015, for developing and teaching the IEEE Tutorial "Energy Forecasting in the Smart Grid Era")

- IEEE PES Technical Council Distinguished Service Award (2014, for organizing Global Energy Forecasting Competition 2012)

Q. Are you sponsoring any exhibits?

A. Yes. I am sponsoring the following exhibits, which were prepared by me or under my supervision and are attached to this pre-filed testimony:

- Exhibit No. __ (TAO-1) - Tao Hong Curriculum Vitae; and
- Exhibit No. __ (TAO-2) - Paper entitled "Long Term Probabilistic Load Forecasting and Normalization With Hourly Information."

Q. What is the purpose of your rebuttal testimony?

A. The purpose of my testimony is to rebut Quantum Pasco Power, L.P.'s witness Dr. Sotkiewicz's claim on page 15 in his direct testimony that "Seminole's forecasting cannot be used a basis for supporting the need for the combined capacity of SCCF and SHCCF." I will briefly discuss fundamental flaws in Dr. Sotkiewicz's analysis of Seminole's forecasting error. I will comment on the error analysis presented in Mr. Wood's rebuttal testimony, which I believe is a better way to evaluate Seminole's current load forecasting methodology. Finally, I will discuss my review of Seminole's forecasting methodology and the resulting models used to generate Seminole's current load forecasts. Based on my independent review of Seminole's forecasting methodology, forecasting system, forecasting process, and the resulting models and forecasts, I believe Seminole's approach to load forecasting is reasonable. The models and forecasts are useful for supporting the determination of need.

Q. In your opinion, is the error analysis presented on pages 14 through 16 of Dr. Sotkiewicz's testimony an appropriate way to evaluate Seminole's current load forecast?

A. No. As discussed in detail in Kyle Wood's rebuttal testimony, Dr. Sotkiewicz's error analysis has three fundamental flaws. First, it is based on data that pre-dates significant changes in Seminole's forecast methodology and, therefore, does not provide any relevant information concerning Seminole's current load forecast. Second, it does not give proper consideration of Lee County Electric Cooperative's departure from Seminole. Third, Dr. Sotkiewicz's analysis does not consider the lead time of the forecasting and planning processes. Because it takes about a year to develop the forecast and then the site plan, the year *x* site plan is using the forecast produced in year *x*-1. As a result, the "three years out" forecast in Dr. Sotkiewicz's analysis is in fact a "four years out" forecast. In general, the longer the forecast horizon is, the more uncertainty and errors are to be expected. For this reason, Dr. Sotkiewicz's analysis greatly exaggerates the error in Seminole's historical forecasts.

Q. Is there a better way than Dr. Sotkiewicz's method to analyze Seminole's load forecast errors?

A. Yes. Given the recent changes in Seminole's forecast methodology, there are two additional steps that provide more useful information than the historical, annual approach that Dr. Sotkiewicz attempted. First, ex post forecasts can be used to tell the accuracy of the model without being distracted by the forecast errors of the predictors. An ex post forecast is the forecast generated with the perfect knowledge of future values of the predictors. For instance, an ex post forecast of next year's load assumes that we know the actual weather and economy condition. Second, evaluation of the forecast accuracy on a higher temporal resolution, such as monthly forecasts, can tell the performance of the model at high granularity and reduce the lucky or unlucky factor at the annual resolution. The ex post forecast analyses provided in Mr. Wood's rebuttal testimony includes these two approaches.

Q. What do you conclude from your review of the additional analyses presented in Mr. Wood's rebuttal testimony?

A. The resulting monthly Absolute Percentage Errors ("APE") range from 2.3% to 3.5% in the demand model and 1.8% to 2.3% in the energy model. I consider these error rates to be reasonably low. For instance, in one of my papers that won the prize paper award from IEEE Power and Energy Society's Power Systems Planning and Implementation Committee, the average Mean Absolute Percentage Error ("MAPE') was 3.3% for monthly peak demand and 1.5% for monthly energy. A copy of that paper is attached as Exhibit No. __ (TAO-2).

Q. Are you familiar with the forecasting methodology and load forecasting models that Seminole used to develop the load forecasts presented in this proceeding?

A. Yes. I have reviewed the files that document Seminole's forecasting methodologies, such as the assumptions, data inputs, and variable selection processes. I have also reviewed Seminole's forecasting models and the resulting forecasts. In addition, I have reviewed portions of Seminole's site plans that are related to load forecasting. The period of my review dates back to 2003. Therefore, I am familiar with the long term load forecasting practice and the major improvements made over past few years at Seminole.

Q. Do you have an opinion regarding the reasonableness of Seminole's forecasting methodology and load forecasting models that Seminole used to develop the load forecasts?

A. Yes. I believe Seminole's approach is reasonable. The factors being considered in Seminole's modeling and forecasting efforts are comprehensive. The resulting models and forecasts are reasonable for use in these proceedings.

As a best-known statistician and time series forecasting guru, George Box, once stated: "all models are wrong, but some are useful." Seminole's forecasts in the early 2010s were higher than the actuals. This is not surprising considering the fact that no one could have predicted the end date of the Great Recession that occurred during the period that Dr. Sotkiewicz analyzed. Even many credible economy forecasts are still overestimating the recovery. On top of the great uncertainties in economy, the weather beyond two weeks is hard to predict. Therefore, I do not believe that the best method is to look at a long term load forecasting model and the forecasts at annual resolution from the aspect of ex ante forecast accuracy. Instead, looking at the ex post forecast accuracy at a higher resolution, i.e., monthly, is a better method.

I am also impressed by the improvement of Seminole's forecasting practice. During the past few years, Seminole's forecasting practice has been improved significantly. For instance, they upgraded their forecasting system from mainframe to Windows. They adopted a state-of-the-art weather station selection methodology to capture the weather patterns more accurately than before. They included end use modeling to capture the new usage patterns. Finally, I would also like to acknowledge that Seminole's current forecasting practice, like most other utilities, still has room for further improvement. For instance, the resolution of the data they are working with can be further increased to hourly data. The long term forecasts can be generated in probabilistic format and evaluated probabilistically. Through the review of Seminole's practice, I believe they are moving toward this direction. They recently installed SAS® Energy Forecasting, a solution that can generate probabilistic load forecasts using hourly data.

Q. Do you agree with Dr. Sotkiewicz's opinion that "Seminole's forecasting cannot be used a basis for supporting the need for the combined capacity of SCCF and SHCCF"?

A. No. I do not agree with Dr. Sotkiewicz's opinion that "Seminole's forecasting cannot be used a basis for supporting the need for the combined capacity of SCCF and SHCCF." (The quote is copied word-by-word from page 15 of his direct testimony.)

The keyword "forecasting" in this statement and many other forecasting-related terminologies throughout his testimony have been misused and sometimes ambiguous. "Forecasting" means the process of figuring out how the future will look like. To be precise in communication, we typically use "forecasting" together with another word, such as "methodology," "system," "process," and "model." On the other hand, "forecast" means how the future will look like, which the result of a forecasting process. Dr. Sotkiewicz misused “forecasting” and “forecast” many times in his testimony, making it difficult for a professional forecaster to interpret what he really meant. Due to the ambiguousness of Dr. Sotkiewicz’s original statement, I would like to answer the question from the following aspects:

- Seminole’s forecasting methodology is sound and reasonable.
- Seminole’s forecasting system, which was upgraded from a mainframe computing environment in 2014, is up-to-date.
- Seminole’s forecasting process is properly managed and traceable.
- Seminole’s forecasting models have considered the important factors for system planning purposes and are reasonable.
- Seminole’s forecasts are reasonable and useful for supporting the need for the combined capacity of SCCF and SHCCF.

Q. Does this conclude your rebuttal testimony?

A. Yes.

Tao Hong
Curriculum Vitae
February 2018

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Appointments

Current Appointments

2017-	Associate Professor (with tenure), Systems Engineering and Engineering Management Department, University of North Carolina at Charlotte, Charlotte, NC
2014-	Owner and Chief Data Scientist, Hong Analytics, Charlotte, NC

Previous Appointments

2013-2017	Assistant Professor and Graduate Program Director, Systems Engineering and Engineering Management Department, University of North Carolina at Charlotte, Charlotte, NC
2013-2013	Senior Industry Consultant, US Energy Business Unit, SAS Institute Inc., Cary, NC
2012-2013	Industry Consultant, US Utilities Business Unit, SAS Institute Inc., Cary, NC
2011-2012	Analytical Consultant, US Retail Professional Services, SAS Institute Inc., Cary, NC
2010-2011	Principal Engineer, Quanta Technology, Raleigh, NC
2009-2010	Senior Engineer, Quanta Technology, Raleigh, NC
2008-2009	Intern/Engineer, Quanta Technology, Raleigh, NC

Education

2010	Ph.D., Operations Research and Electrical Engineering, North Carolina State University
2008	M.S., Operations Research and Industrial Engineering, North Carolina State University
2008	M.S., Electrical Engineering, North Carolina State University
2005	B.Eng., Automation, Tsinghua University, Beijing, China

Awards and Honors

2017	Charlotte Business Journal Energy Education Leader of the Year
2016	IEEE Power & Energy Society Technical Committee Prize Paper Award
2015	IEEE Power & Energy Society Technical Committee Working Group Recognition Award
2015	Global Energy Forecasting Competition 2014 Institute Prize
2014	IEEE Power & Energy Society Technical Council Distinguished Service Award

Teaching

Courses at UNC Charlotte

1. SEGR4961/EMGT5961 Introduction to Energy Systems
2. SEGR4963/EMGT5963 Energy Systems Planning
3. SEGR4964/EMGT5964 Case Studies in the Energy Industry
4. EMGT6910 Technological Forecasting and Decision Making
5. EMGT6965 Energy Analytics
6. EMGT6980 Engineering Management Project

Courses at Hong Analytics

1. T101 Fundamentals of Utility Analytics: Techniques, Applications and Case Studies
2. T201 Introduction to Energy Forecasting
3. T302 Long Term Load Forecasting
4. T303 Power Distribution Outage Analytics
5. T401 Electric Load Forecasting II: Advanced Topics and Case Studies

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Publications

Scholarly Journal Papers

1. Yi Wang, Qixin Chen, Tao Hong, and Chongqing Kang, "Review of smart meter data analytics: applications, methodologies, and challenges," IEEE Transactions on Smart Grid, in press.
2. Jingrui Xie and Tao Hong, "Variable selection methods for probabilistic load forecasting: empirical evidence from seven states of the United States," IEEE Transactions on Smart Grid, in press, available online.
3. Jingrui Xie and Tao Hong, "Temperature scenario generation for probabilistic load forecasting," IEEE Transactions on Smart Grid, in press, available online.
4. Jingrui Xie and Tao Hong, "Load forecasting using 24 solar terms," Journal of Modern Power Systems and Clean Energy, in press, available online.
5. Jian Luo, Tao Hong and Meng Yue, "Real-time anomaly detection for very short-term load forecasting," Journal of Modern Power Systems and Clean Energy, in press, available online.
6. Jian Luo, Tao Hong and Shu-Cherng Fang, "Benchmarking robustness of load forecasting models under data integrity attacks," International Journal of Forecasting, vol.34, no.1. pp 89-104, January-March 2018
7. Qiaochu He and Tao Hong, "Integrated facility location and production scheduling in multi-generation energy systems," Operations Research Letters, vol.46, no.1, pp 153-157, January 2018.
8. Jingrui Xie, Ying Chen, Tao Hong and Thomas D. Laing, "Relative humidity for load forecasting models," IEEE Transactions on Smart Grid, vol.9, no.1, pp 191-198, January 2018.
9. Jingrui Xie and Tao Hong, "Wind speed for load forecasting models", Sustainability, vol 9, no 5, pp 795, May, 2017
10. Jingrui Xie, Tao Hong, Thomas D. Laing and Chongqing Kang, "On normality assumption in residual simulation for probabilistic load forecasting", IEEE Transactions on Smart Grid, vol.8, no.3, pp 1046-1053, May, 2017.
11. Bidong Liu, Jakub Nowotarski, Tao Hong and Rafal Weron, "Probabilistic load forecasting via quantile regression averaging on sister forecasts", IEEE Transactions on Smart Grid, vol.8, no.2, pp 730-737, March, 2017.
12. Jingrui Xie and Tao Hong, "GEFCom2014 probabilistic electric load forecasting: an integrated solution with forecast combination and residual simulation", International Journal of Forecasting, vol.32, no.3, pp 1012-1016, July-September, 2016.
13. Tao Hong and Shu Fan, "Probabilistic electric load forecasting: a tutorial review", International Journal of Forecasting, vol.32, no.3, pp 914-938, July-September, 2016.
14. Tao Hong, Pierre Pinson, Shu Fan, Hamidreza Zareipour, Alberto Troccoli and Rob J. Hyndman, "Probabilistic energy forecasting: Global Energy Forecasting Competition 2014 and beyond", International Journal of Forecasting, vol.32, no.3, pp 896-913, July-September, 2016.
15. Pu Wang, Bidong Liu and Tao Hong, "Electric load forecasting with recency effect: a big data approach", International Journal of Forecasting, vol.32, no.3, pp 585-597, July-September, 2016.
16. Jakub Nowotarski, Bidong Liu, Rafal Weron and Tao Hong, "Improving short term load forecast accuracy via combining sister forecasts", Energy, vol.98, pp 40-49, March 1, 2016.
17. Jingrui Xie, Tao Hong and Joshua Stroud, "Long term retail energy forecasting with consideration of residential customer attrition", IEEE Transactions on Smart Grid, vol.6, no.5, pp. 2245-2252, September, 2015.
18. Tao Hong, Pu Wang and Laura White, "Weather station selection for electric load forecasting", International Journal of Forecasting, vol.31, no.2, pp 286-295, April-June, 2015.
19. Tao Hong, Pierre Pinson and Shu Fan, "Global energy forecasting competition 2012", International Journal of Forecasting, vol.30, no.2, pp 357-363, April-June, 2014.
20. Tao Hong and Pu Wang, "Fuzzy interaction regression for short term load forecasting", Fuzzy Optimization and Decision Making, vol.13, no.1, pp. 91-103, March, 2014.
21. Tao Hong, Jason Wilson and Jingrui Xie, "Long term probabilistic load forecasting and normalization with hourly information", IEEE Transactions on Smart Grid, vol.5, no.1, pp.456-462, January, 2014.

Journal Editorials

1. Tao Hong, Chen Chen, Jianwei Huang, Ning Lu, Le Xie and Hamidreza Zareipour, "Guest Editorial: big data analytics for grid modernization", IEEE Transactions on Smart Grid, vol.7, no.5, pp 2395-2396, September, 2016.

2. Tao Hong, Shu Fan, Wei-Jen Lee, Wenyuan Li, Anil Pahwa, Pierre Pinson, Jianhui Wang and Hamidreza Zareipour, "Guest editorial: special section on Analytics for energy forecasting with applications to smart grid", IEEE Transactions on Smart Grid, vol.5, no.1, pp. 399-401, January, 2014.

Trade Journal and Magazine Papers

1. Jonathan Black, Alex Hofmann, Tao Hong, Joseph Roberts, and Pu Wang, "Weather data for energy analytics: from modeling outages and reliability indices to simulating distributed photovoltaic fleets," accepted by Power and Energy Magazine.
2. Tao Hong, David Gao, Tom Laing, Dale Kruchten, and Jorge Calzada, "Producing energy data scientists," accepted by Power and Energy Magazine.
3. Tao Hong, "Big data analytics: making smart grid smarter" accepted by Power and Energy Magazine.
4. Jingrui Xie and Tao Hong, "Improving gas load forecasts with big data", Natural Gas & Electricity, vol.32, no.10, pp 25-30, May, 2016.
5. Tao Hong, "Crystal ball lessons in predictive analytics", EnergyBiz, pp. 35-37, Spring, 2015
6. Tao Hong, "Integrated energy forecasting: improving T&D planning and operations." Electricity Today, pp. 58-62, January/February, 2015
7. Tao Hong, "How to juggle the analytics of forecasting: 13 lucky tips", Intelligent Utility, pp. 11-13, July/August, 2014
8. Tao Hong, "Energy forecasting: past, present and future", Foresight: The International Journal of Applied Forecasting, issue 32, pp. 43-48, Winter 2014.
9. Tao Hong and Alyssa Farrell, "Utilities dust off the forecasting playbook: smart grid data brings challenges and opportunities", Analytics Magazine, pp.50-57, July/August, 2013

Thesis & Dissertation

1. Tao Hong, "Short Term Electric Load Forecasting". PhD dissertation, North Carolina State University, Sep 10th, 2010
2. Tao Hong, "Long-Term Spatial Load Forecasting Using Human Machine Co-construct Intelligence Framework". Master thesis, North Carolina State University, Oct 28th, 2008

White Papers

1. Tao Hong and Mohammad Shahidehpour, "Load forecasting case study", National Association of Regulatory Utility Commissioners, pp.1-171, 2015.
2. Sen-Hao Lai and Tao Hong, "When one size no longer fits all: electric load forecasting with a geographic hierarchy", SAS White Paper, pp.1-14, 2013

Conference Proceedings

1. Antonio Bracale, Guido Carpinelli, Pasquale De Falco and Tao Hong, "Short-term industrial load forecasting: a case study in an Italian factory," 2017 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe), Torino, Italy, September 26-29, 2017
2. Jingrui Xie and Tao Hong, "Comparing two model selection frameworks for probabilistic load forecasting", 2016 International Conference on Probabilistic Methods Applied to Power Systems, Beijing, China, October 16-20, 2016
3. Jingrui Xie; Tao Hong and Chongqing Kang "From high-resolution data to high-resolution probabilistic load forecasts", 2016 IEEE PES Transmission and Distribution Conference and Exposition, Dallas, TX, May 2-5, 2016
4. Jingrui Xie, Bidong Liu, Xiaoqian Lyu, Tao Hong, and David Basterfield, "Combining load forecasts from independent experts: experience at NPower forecasting challenge 2015", the 47th North American Power Symposium (NAPS2015), Charlotte, NC, October 4 - 6, 2015
5. Tao Hong, Tom Laing and Pu Wang, "Four best practices of load forecasting for electric cooperatives", 2014 IEEE Rural Electric Power Conference, Fort Worth, Texas, May 18 - 21, 2014
6. Tao Hong and Pu Wang, "On the impact of demand response: load shedding, energy conservation, and further implications to load forecasting", 2012 IEEE PES General Meeting, San Diego, CA, July 19-22, 2012
7. Tao Hong; Pu Wang, and H. Lee Willis, "A naive multiple linear regression benchmark for short term load forecasting," 2011 IEEE PES General Meeting, Detroit, MI, July 24-29, 2011

8. Tao Hong; Min Gui; Mesut E. Baran; H. Lee Willis , "Modeling and forecasting hourly electric load by multiple linear regression with interactions," Power and Energy Society General Meeting, 2010 IEEE , vol., no., pp.1-8, July 25-29, 2010
9. Tao Hong; Pu Wang; Anil Pahwa; Min Gui; Simon M. Hsiang, "Cost of temperature history data uncertainties in short term electric load forecasting," Probabilistic Methods Applied to Power Systems (PMAPS), 2010 IEEE 11th International Conference on , vol., no., pp.212-217, June 14-17, 2010
10. Tao Hong; James J Burke, "Calculating line losses in smart grid: A new rule of thumb," 2010 IEEE PES Transmission and Distribution Conference and Exposition, April 19-22, 2010
11. Tao Hong; Hsiang, S.M.; Le Xu; , "Human-machine co-construct intelligence on horizon year load in long term spatial load forecasting," IEEE Power & Energy Society General Meeting, July 26-30, 2009
12. Tao Hong and Mo-Yuen Chow, "Resource allocation for a life science automation line: a Petri nets approach". Proceedings of CASE07, the 3rd Annual IEEE Conference on Automation Science and Engineering, pp 255-260, Scottsdale, AZ, USA, September 22-25, 2007
13. Tao Hong, Mo-Yuen Chow, Perry Haaland, Dylan Wilson and Robert Walker "Scheduling a life science high-throughput platform under starvation constraints using timed transition Petri nets and heuristic search". Proceedings of ISIE07, 2007 IEEE International Symposium on Industrial Electronics, Vigo, Spain, June 4-7, 2007
14. Tao Hong and Mo-Yuen Chow, "Timed Petri nets modelling of high-throughput screening process for fault study", Proceedings of IECON06, The 32nd Annual Conference of the IEEE Industrial Electronics Society, pp 4425-4430, Paris, France, November 7-10, 2006
15. Yunfei Wang, Geng Yang and Tao Hong, "Analysis and implementation of AC motor braking method without energy returning or braking unit", The 8th International Conference on Electrical Machines and Systems (ICEMS 2005), Volume II, pp 1447-1451, Nanjing, China, September 27-29, 2005.

Talks

Keynotes

1. "Sharing in Power & Energy Grids," 2017 Workshop on Network Economy and Big Data, Beijing, China, December 17, 2017.
2. "Probabilistic Load Forecasting: Past, Present and Future", The 2nd International Conference on Forecasting Economic and Financial Systems, Beijing, China, October 30 - November 1, 2015
3. "Big Data Analytics for Grid Modernization", 2014 Electric System Brazilian Symposium (SBSE2014), Paraná, Brazil, April 22-25, 2014

Tutorials

1. "Energy Forecasting in the Smart Grid Era", Tutorial at 2016 IEEE PES General Meeting, Boston, MA, July 17-21, 2016 (with Hamidreza Zareipour and Pierre Pinson)
2. "Energy Forecasting in the Smart Grid Era", Tutorial at 2015 IEEE PES General Meeting, Denver, CO, July 26-30, 2015 (with Shu Fan and Hamidreza Zareipour)
3. "Energy Forecasting in the Smart Grid Era", Tutorial at 2014 IEEE PES General Meeting, National Harbor, MD, July 27-31, 2014 (with Hamidreza Zareipour)
4. "100 Years of Load Forecasting: Classics, Challenges, and Best Practices with Smart Grid Information", 2014 Electric System Brazilian Symposium (SBSE2014), Paraná, Brazil, April 22-25, 2014
5. "Energy Forecasting in the Smart Grid Era", Tutorial at 2013 IEEE PES General Meeting, Vancouver, BC, Canada, July 21-25, 2013 (with Shu Fan, Hamidreza Zareipour and Pierre Pinson)
6. "100 Years of Load Forecasting: Classics, Challenges, and Best Practices with Smart Grid Information", Pre-conference Workshop at Western Load Research Association Conference, Long Beach, CA, Oct 9, 2012

Conference Presentations

1. "Lessons Learned from the Open Data Track of Global Energy Forecasting Competition 2017", 2017 IEEE PES General Meeting, Chicago, IL, July 16 - 20, 2017
2. "Research Trends in Load Forecasting and Their Implications to Energy Trading", 2017 IEEE PES General Meeting, Chicago, IL, July 16 - 20, 2017

3. "Forecasting Load of New England Using 24 Solar Terms of China", 2017 International Symposium on Energy Analytics, Cairns, Australia, June 22 - 23, 2017
4. “Load Forecasting with Big Models: the Surprising Accuracy Improvement from Big Computers”, 2016 AEIC Load Research Conference and WLRA Fall Conference, Chicago, IL, September 18 - 21, 2016
5. “Energy Forecasting: Past, Present and Future”, Southwest Forecasting & Customer Analytics Forum, Tucson, AZ, September 15 - 16, 2016
6. "What's New in Load Forecasting since 2010?", 2016 IEEE PES General Meeting, Boston, MA, July 17 - 21, 2016
7. "What's New in Load Forecasting since 2010?", 36th International Symposium on Forecasting, Santander, Spain, June 19 - 22, 2016
8. “Lessons Learned from Organizing Energy Forecasting Competitions”, ARPA-E GRID DATA Kick-off Meeting, Denver, CO, March 30 - 31, 2016
9. "Analytics, Smart Grid and Big Data: Are They Like Teenage Sex?", 2015 CAPER Summer Research Planning Workshop, Boone, NC, August 27 - 28, 2015
10. "Weather Station Selection for Load Forecasting", 2015 AEIC Load Research Conference and WLRA Fall Conference, Chicago, IL, August 23 - 26, 2015
11. "GEFCom2014 Institute Prize - University of North Carolina at Charlotte", 2015 IEEE PES General Meeting, Denver, Colorado, July 26-30, 2015
12. "How does Relative Humidity Affect Electricity Demand?", 3rd International Conference on Energy & Meteorology, Boulder, Colorado, June 22 - 26, 2015
13. "Electricity Demand Interval Forecasting With Quantile Regression Averaging", 35th International Symposium on Forecasting, Riverside, California, June 21 - 24, 2015
14. "The Myths Of Residual Simulation For Probabilistic Load Forecasting", 35th International Symposium on Forecasting, Riverside, California, June 21 - 24, 2015
15. "Combining Sister Load Forecasts", 35th International Symposium on Forecasting, Riverside, California, June 21 - 24, 2015
16. "Load Forecasting with Energy Efficiency: Challenges and Fundamentals", 2015 OPSI Spring Meeting, Phoenixville, PA, April 13, 2015
17. "A Crowdsourcing Approach to Energy Forecasting", 2014 Great Lakes Symposium on Smart Grid and the New Energy Economy, Chicago, IL, September 22-25, 2014
18. "The Art and Science of Reconciliation in Long Term Load Forecasting", 2014 AEIC Load Research Conference and WLRA Fall Conference, Chicago, IL, September 21-24, 2014
19. "Combining Load Forecasts from Multiple Vendors", 2014 IEEE PES General Meeting, National Harbor, MD, July 27-31, 2014
20. "Energy Forecasting Competition: Past, Present and Future", 34th International Symposium on Forecasting, Rotterdam, The Netherlands, June 29 - July 2, 2014
21. "Understanding Electricity Consumer Behavior through Smart Meter Data", NSF Workshop on Understanding Human Behaviors for Sustainable Building Ecosystems, Charlotte, NC, May 27, 2014
22. "Four Best Practices of Load Forecasting for Electric Coorperatives", 2014 IEEE Rural Electric Power Conference, Fort Worth, TX, May 18 - 21, 2014
23. "Integrating Energy Forecasts into Utility Planning and Operations: Perspectives from Market Participants", 2014 IEEE PES T&D Conference & Exposition, Chicago, IL, April 14-17, 2014
24. "Forecasting in the Smart Grid Era", Utility Analytics Summit, Raleigh-Durham, NC, April 9-11, 2014
25. "Modernization of Electric Load Forecasting", Eastern Interconnection States' Planning Council Meeting: Approaches to Load Forecasting, Naples, FL, March 13-14, 2014
26. "Driving the Value of Smart Grid Data through Predictive Analytics", The 5th Innovative Smart Grid Technologies Conference, Washington DC, February 19-22, 2014
27. "Load Forecasting in the Smart Grid Era", 2013 Technology Conference, Myrtle Beach, SC, August 7-9, 2013 (with Jason Wilson, download presentation slides)
28. "Opportunities and Challenges of Energy Forecasting in the Smart Grid Era", 2013 IEEE PES General Meeting, Vancouver, BC, Canada, July 21-25, 2013
29. "Global Energy Forecasting Competition: An Introduction", 2013 IEEE PES General Meeting, Vancouver, BC, Canada, July 21-25, 2013
30. "Three Myths about Weather Normalization", AEIC Load Research Conference, Alexandria, VA, July 7-10, 2013

31. "Modernization of Long Term Load Forecasting: An Integrated Approach Taking Advantage of Hourly Load and Weather Information", Electric Utility Forecasters Forum, Orlando, FL, November 8, 2012
32. "When Predictive Analytics Meets Smart Grid: Electric Load Forecasting with Geographic Hierarchy", 2012 SAS Analytics Conference, Las Vegas, NV, October 8-9, 2012 (with Sen-hao Lai)
33. "Modernization of Long Term Load Forecasting: An Integrated Approach Taking Advantage of Hourly Load and Weather Information", AEIC Load Research Conference, July 9, Alexandria, VA, 2012
34. "Electric Load Forecasting with Holiday Effect", AEIC 2012 Load Research Workshop, Orlando, FL, March 18, 2012
35. "On the Holiday Effect of Electricity Demand", 2011 SAS Analytics Conference, October 24-25, Orlando, FL, 2011
36. "Rethinking Short Term Electric Load Forecasting: Experience at US Utilities," 2011 INFORMS Conference on Business Analytics and Operations Research, Chicago, IL, April 10-12, 2011
37. "Behavior Mining of Electric Load Consumption: A Regression Approach", SAS' 12th Annual Data Mining Conference, M2009, Las Vegas, NV, October 26-27, 2009
38. "Electric Load Forecasting: Two Perspectives", INFORMS Annual Meeting, San Diego, CA, October 11-14, 2009

Services

Editorial Services

2017-	Associate Editor, Journal of Modern Power and Clean Energy
2016-	Editor, Book Series on Energy Analytics, CRC Press
2016-	Associate Editor, International Journal of Forecasting
2016-	Editorial Board Member, Power & Energy Magazine
2015-	Associate Editor, International Journal of Energy Technology and Policy
2013-	Editor, IEEE Transactions on Smart Grid
2014-2016	Guest Editor-in-Chief, Special Section on Big Data Analytics for Grid Modernizations, IEEE Transactions on Smart Grid
2014-2016	Guest Editor, Special Section on Probabilistic Energy Forecasting, International Journal of Forecasting
2012-2014	Guest Editor, Special Section on Energy Forecasting, International Journal of Forecasting
2012-2014	Guest Editor-in-Chief, Special Section on Analytics for Energy Forecasting with Applications to Smart Grid, IEEE Transactions on Smart Grid

Professional Organization Services

2011-	Chair, IEEE Working Group on Energy Forecasting
2012-	General Chair, Global Energy Forecasting Competition
2011-2016	Member, IEEE Power Systems Planning and Implementation Committee

Conference Chair

2017	International Symposium on Energy Analytics (ISEA2017)

Session Chair

2017	"Accommodating Intermittent Renewable Energy by Multiple Energy Systems Integration: Forecasting, Operations and Planning", PESGM2017
2017	"Featured Session - Renewable Energy Forecasting: Nonlinearity, Dimensionality and Sharing Aspects", ISF2017
2016	"Load Forecasting: Research Progress and Challenges", ISF2016
2016	"Energy Forecasting 3". ISF2016
2015	"Global Energy Forecasting Competition 2014: An Overview", PESGM 2015
2015	"Global Energy Forecasting Competition 2014: Finalist Presentations", PESGM 2015
2015	"Frontiers in Electricity Demand Forecasting I: The State of The Practice", ISF 2015
2015	"Frontiers in Electricity Demand Forecasting II: Probabilistic Electric Load Forecasting", ISF 2015
2014	"Load Forecasting: the State of the Practice", PESGM 2014
2014	"Electricity Demand II", ISF 2014

2014	"Integrating Energy Forecasts into Utility Planning and Operations: Perspectives from Market Operators", T&D 2014
2014	"Integrating Energy Forecasts into Utility Planning and Operations: Perspectives from Market Participants", T&D 2014
2013	"Energy Forecasting: the State of the Art", PESGM 2013
2013	"Global Energy Forecasting Competition Final Presentations", PESGM 2013
2012	"Demand Response: Analytics, Practice, and Challenges in Smart Grid Environment", PESGM 2012
2012	"Load Forecasting Methodologies and Applications in Operations and Planning", PESGM 2012
2011	"Practical Aspects of Electric Load Forecasting", PESGM 2011
2009	"Forecasting", INFORMS 2009

Technical Program Committee Member

2013-	International Conference Energy & Meteorology 2015, 2017 & 2018
2010-	IEEE Power & Energy Society General Meeting
2010-	IEEE T&D Conference and Expositions
2015	2nd International Conference on Forecasting Economic and Financial Systems (FEFS2015)
2015	Modern Electric Power Systems conference 2015 (MEPS'15)
2014	33rd IEEE. International Performance Computing and Communications Conference (IPCCC2014)
2014	IEEE International Conference on Internet of Things (iThings2014)
2014	IEEE Innovative Smart Grid Technologies Conference 2014 (ISGT2014)

Long Term Probabilistic Load Forecasting and Normalization With Hourly Information

Tao Hong, Jason Wilson, *Member, IEEE*, and Jingrui Xie, *Associate Member, IEEE*

***Abstract*—The classical approach to long term load forecasting is often limited to the use of load and weather information occurring with monthly or annual frequency. This low resolution, infrequent data can sometimes lead to inaccurate forecasts. Load forecasters often have a hard time explaining the errors based on the limited information available through the low resolution data. The increasing usage of smart grid and advanced metering infrastructure (AMI) technologies provides the utility load forecasters with high resolution, layered information to improve the load forecasting process. In this paper, we propose a modern approach that takes advantage of hourly information to create more accurate and defensible forecasts. The proposed approach has been deployed across many U.S. utilities, including a recent implementation at North Carolina Electric Membership Corporation (NCEMC), which is used as the case study in this paper. Three key elements of long term load forecasting are being modernized: predictive modeling, scenario analysis, and weather normalization. We first show the superior accuracy of the predictive models attained from hourly data, over the classical methods of forecasting using monthly or annual peak data. We then develop probabilistic forecasts through cross scenario analysis. Finally, we illustrate the concept of load normalization and normalize the load using the proposed hourly models.**

***Index Terms*—Load forecasting, load normalization, multiple linear regression models, weather normalization.**

I. Nomenclature

GSP: Gross state product.

CDD: Cooling degree days.

HDD: Heating degree days.

Trend: A linear trend variable.

$T_{\max}$: Monthly peak temperature.

T_t: Current hour temperature.

T_{t-k}: Temperature of the previous kth hour.

T_a: Average temperature of the past 24 hours.

Month: Class variable, 12 months of the year.

Weekday: Class variable, 7 days of a week.

Hour: Class variable, 24 hours of a day.

Day: Class variable, code for days of a year.

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Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

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II. Introduction

LONG TERM LOAD forecasting (LTLF) provides peak demand and energy forecasts for one or more years, and can be expanded out to a horizon of a few decades. Utilities typically produce long term forecasts ranging from 20 to 50 years into the future. Such forecasts are often being used for planning by multiple departments in a utility, such as system planning, finance, demand side management, and power supply, etc. North Carolina Electric Membership Corporation (NCEMC), is one of the largest electric generation cooperatives in the U.S., and is comprised of a family of corporations formed to support 26 of North Carolina's electric distribution cooperatives. These cooperatives provide energy and related services to more than 950 000 households and businesses in 93 of North Carolina's 100 counties. At NCEMC, long term load forecasts serve as the important inputs to the power supply group to support decisions on electricity purchase contracts. Because NCEMC owns generation units, it is required to file Integrated Resource Planning (IRP) documents with the North Carolina Public Utilities Commission, thus expanding the scrutiny from the member cooperatives and NCEMC board, to the state regulatory commission.

In the regulatory environment, utility forecasters have to defend the long term forecasts internally to the utility's management and externally to the regulatory commission. Although forecasting by nature is a stochastic problem, most utilities today are still developing and using point forecasts instead of probabilistic forecasts. Due to the poor predictability of the climate, which is a main driver of electricity demand, it is unrealistic and unfair to judge a long term forecaster by comparing a few years of point forecasts with the corresponding actual values. Instead, there are two important questions that should be asked and answered properly when defending the long term forecasts: 1) *is the current scenario covered by the forecasts?* 2) *how accurate is the forecast given the current scenario?*

Most utilities today follow the LTLF practices similar to the ones established a few decades ago, when there was not high resolution data available. Since the type of low resolution data used in the traditional approach provides a limited number of observations for predictive modeling, the forecasters may not be able to use enough explanatory variables to capture all the salient features of electric load. When given the actual values of the weather and economy variables to re-forecast the loads under the current scenario, the model may still produce some significant errors, which can be hard to explain by the forecasters.

There are a few ways to create weather scenarios for LTLF and weather normalization. A lot of utilities are using the average temperature profile (in hourly or daily interval for a year) from the previous few decades as the normal weather to derive the normal load, which is not a defensible approach: 1) an average temperature profile understates the peaks, so it can not accurately represent the normal weather; 2) a normal weather profile may not lead to a normal load profile due to the nonlinear relationship between the load and weather [1]. Another popular approach is to use normal or typical weather profiles created by third parties, such as National Oceanic and Atmospheric Administration (NOAA) and the U.S. Department of Energy (DOE). An advantage of this third-party profile approach is its simplicity. However, these weather profiles are not created specifically for utilities to calculate normalized load. Therefore, it is questionable that their best use is for normalizing the load profile in the utility industry. A more rigorous approach is based on Monte Carlo simulation, which is often adopted by the risk management teams in the utility industry. The quantitative risk analysts first analyze the distribution of temperatures on each hour of the year. They then create thousands of temperature profiles for scenario analysis. This simulation approach requires a lot of computational resources. The results, including thousands of load profiles, are sometimes too voluminous and become difficult to understand and be used by the system operators in practice.

Most literature in the load forecasting field has been devoted to short term load forecasting, of which the forecasting horizon is two weeks or less [1]–[7]. Not many papers have been devoted to LTLF, of which few papers present practical approaches verified through field implementations at utilities. An implementation of spatial load forecasting work at Madison Gas and Electric Company has been presented in [8]–[10]. A peak load forecasting methodology implemented at Australian Energy Market Operator (AEMO) has been reported in [11]. In this paper, we propose a probabilistic forecasting approach with hourly data, which is the continuation of Hong's load forecasting methodology presented in [1]. We dissect LTLF to three elements: predictive modeling, scenario analysis, and weather normalization. We then modernize each step with multiple linear regression (MLR) models and hourly data. The proposed approach has been deployed to many large and medium size utilities including NCEMC. The data required in the NCEMC case study includes hourly system load data at corporate level, which is available through NCEMC's Energy Management System, hourly weather data purchased from WeatherBank and annual economy data purchased from Moody's. Execution of the proposed approach on NCEMC data in automated mode can be finished within a day on a commodity server with an 8-core CPU and 32G RAM. This is well-acceptable for a once-per-year long term load forecasting task. In comparison with Fan's approach, which originated from a field implementation at an ISO, the approach proposed in this paper is more applicable to utilities operating within a regulatory environment, due to its relative simplicity and strong defensibility. The scope of this paper does not include forecasting under renewable penetration and demand response activities.

TABLE I
MAIN AND CROSS EFFECTS OF THE STARTING MODELS

Model	Main Effects	Cross Effects
C1	*GSP, CDD, HDD, Month*	N/A
C2	*GSP*, $T_{\max}$, $T_{\max}^2$, $T_{\max}^3$, *Month*	N/A
B	*Trend*, T_t, T_t^2, T_t^3, *Month, Weekday, Hour*	T_t**Month*, T_t^2**Month*, T_t^3**Month*, T_t**Hour*, T_t^2**Hour*, T_t^3**Hour*, *Weekday*Hour*
S2010	*Trend*, T_t, T_t^2, T_t^3, T_{t-1}, T_{t-1}^2, T_{t-1}^3, T_{t-2}, T_{t-2}^2, T_{t-2}^3, T_{t-3}, T_{t-3}^2, T_{t-3}^3, T_a, T_a^2, T_a^3, *Month, Day, Hour*	T_t**Month*, T_t^2**Month*, T_t^3**Month*, T_t**Hour*, T_t^2**Hour*, T_t^3**Hour*, T_{t-1}**Month*, T_{t-1}^2**Month*, T_{t-1}^3**Month*, T_{t-1}**Hour*, T_{t-1}^2**Hour*, T_{t-1}^3**Hour*, T_{t-2}**Month*, T_{t-2}^2**Month*, T_{t-2}^3**Month*, T_{t-2}**Hour*, T_{t-2}^2**Hour*, T_{t-2}^3**Hour*, T_{t-3}**Month*, T_{t-3}^2**Month*, T_{t-3}^3**Month*, T_{t-3}**Hour*, T_{t-3}^2**Hour*, T_{t-3}^3**Hour*, T_a**Month*, T_a^2**Month*, T_a^3**Month*, T_a**Hour*, T_a^2**Hour*, T_a^3**Hour*, *Day*Hour*,

The rest of the paper is organized as follows: Section III reviews the fundamentals, including the models we start with; Section IV discusses the model selection approach and determines the length of historical data used in long term forecasting; Section V presents the long term probabilistic forecasts with cross weather and economy scenarios; Section VI introduces the methodology for load normalization; the paper is concluded in Section VI with discussions of potential future work.

III. FUNDAMENTALS

A. Multiple Linear Regression

Multiple linear regression analysis has been widely used in the forecasting fields, including load forecasting. Detailed coverage on the theory of regression analysis and linear models is provided in [13]. Implementation of MLR in SAS is presented in [14]. A comprehensive guideline about how to apply MLR models to short term load forecasting is discussed in [1].

In this case study, we start with several MLR models: a classical model for monthly energy forecasting denoted as $C1$, a classical model for monthly peak forecasting denoted as $C2$, Tao's vanilla benchmark denoted as B, and a group of customized short term load forecasting models denoted as S. The models in S are derived using Hong's methodology documented in [1], where by default, 3 years of data are used for parameter estimation and the year after is used for variable selection. When using year 2010 for variable selection, we denote the resulting variable combination as S_{2010}. All of these starting models have the dependent variable *Load* and an intercept term. The main effects and cross effects are described in Table I, where each class variables consists of several 0–1 indicator variables. S_{2010} is used as an example of S models.

TABLE II
MODIFICATIONS TO THE DAYS OF A YEAR FOR MODEL S_{2010}

Days of a Year (Original)	Day Code (Modified)
Wednesday (regular)	Tuesday
Day Before New Year's Day	Saturday
New Year's Day	Friday → Saturday; else → Sunday
Memorial Day	Saturday
Day After Memorial Day	Monday
Day Before Independence Day	Friday
Independence Day	Friday → Saturday; else → Sunday
Day Before Labor Day	Saturday
Labor Day	Saturday
Day After Labor Day	Thursday
Day Before Thanksgiving Day	Monday
Thanksgiving Day	Saturday
Day After Thanksgiving Day	Saturday
Day Before Christmas Day	Saturday
Christmas Day	Friday → Saturday; else → Sunday
Day After Christmas Day	Saturday

The *Day* variable is derived from the *Weekday* variable using rules described in Table II. We first group Tuesday and Wednesday together labeled as Tuesday. We then model some holidays and the surrounding days using weekdays and weekends [1]. For example, take New Year's Day: it is a fixed-date holiday. When it falls on a Friday, we modify the value of the *Day* variable to Saturday. Otherwise, we model it as a Sunday. We also model the day before New Year's Day as a Saturday.

B. Error Statistics

Despite of many criticisms, mean absolute percentage error (MAPE) is still a widely used error statistic in business forecasting. MAPE (%) can be calculated as follows:

$$MAPE = \frac{100}{N} \sum_{i=1}^{N} |(A_i - P_i)/A_i|, \tag{1}$$

where N is the number of observations, A_i represents the actual load, and P_i represents the predicted load.

Since the results of our case study are monthly energy forecasts and monthly peak forecasts, we also use the MAPE of monthly energy and MAPE of monthly peak to evaluate the forecasting accuracy. To calculate MAPE of monthly energy (or peak) based on hourly load forecasts, we have to first extract the actual and predicted monthly energy (or peak), and then apply (1) to the resulting series.

To properly answer the second question posted in Section II, the forecasts have to be evaluated based on ex post forecasting accuracy. Take one year ahead forecasting for example as covered in Section V. Assuming we are forecasting the monthly peaks of 2011, if we use the information available through the end of 2010 to forecast 2011, the resulting forecast is ex ante forecast, or "before the event" forecast. If we use the information available through the end of 2011 other than the loads of 2011 to forecast the loads of 2011, the resulting forecast is ex post forecast, or "after the event" forecast. At the beginning of 2012, instead of focusing on ex ante forecast of 2011, we should emphasize the ex post forecasting accuracy of 2011, which tells how the model behaves given the actual temperatures of 2011.

IV. PREDICTIVE MODELING

In this section, we first augment the S models to LTLF models, denoted as L, using the available data on and prior to 2006. We then determine the appropriate length of history for one year ahead load forecasting. At the end, we compare the ex post forecasting accuracy of the $C1, C2, B, S,$ and L models on a rolling basis using 2007 through 2010 [15].

A. Model Selection

The general health of the economy is what ultimately drives long term electricity consumption. We would like to extend the model group S for long term forecasting by adding a macroeconomic indicator, *GSP*. The same annual value of GSP is assigned to each hour of a year. We use *GSP* in this paper mainly due to two reasons: 1) the territory of NCEMC covers most of North Carolina, which makes *GSP* a good driver of the NCEMC's long term load; 2) *GSP* is easy to access and understand. If the utility's territory covers one or a few counties or cities, *GDP* (gross domestic product) by county or *GMP* (gross metropolitan product) can be used as the macroeconomic indicator. In practice, depending upon the drivers of the load, we can also use several other indicators and their combinations, such as housing stock, employment rate, number of jobs, etc. For the utilities, especially retail electricity providers, who provide services in deregulated environment, the total loads are highly impacted by customer churn. In those situations, we can use customer count as the macroeconomic indicator.

The augmentation to a long term forecasting model can be achieved in three ways:

1) Replace *Trend* by *GSP*. There is an inherent assumption in this approach: the loads sensitive to weather and calendar stay in the same profile over time, while there is part of a base load that growing linearly in proportion to the economic growth. If the forecasting horizon is within a few years, this approach can be a good approximation in practice. As the horizon becomes longer, there can be significantly more customers moving into the territory. Consequently, the weather and calendar sensitive loads should grow as well.
2) Divide *Load* by *GSP*. The inherent assumption for this approach is that the load is growing at exactly the same rate as the economic growth. In other words, there is no base load that stays constant while the economy is growing. Take a residential community as a counterexample. Before everyone moves in, the feeders, transformers, and street lights are already placed in the community, which lead to a small base load, including no-load loss of transformers, street lighting load, etc. As people are moving in during the next a few years, the total load of this system is growing. However, the small base load stays almost the same since day one. Several ways to extend this approach are to take the natural log or square root of the load or macroeconomic indicator, or both in some combination before performing the division, which allows load to grow faster or slower than the economy.
3) Replace *trend* by *GSP* and then add interactions between *GSP* and the existing main and cross effects. This approach

TABLE III
COMPARISON AMONG THREE WAYS TO ADD GSP ON MAPE OF HOURLY LOAD

Extension	2002	2003	2004	2005	2006	Average
1	4.3	4.2	4.9	6.3	3.7	**4.7**
2	3.6	3.6	3.7	7.5	8.3	5.3
3	4.2	4.7	4.9	6.8	4.3	5.0

TABLE IV
COMPARISON AMONG DIFFERENT LENGTH OF HISTORICAL DATA

Length (yr)	2002	2003	2004	2005	2006	Average
1	4.9	5.5	4.6	4.1	4.7	4.8
2	3.6	4.2	4.8	5.1	3.5	**4.2**
3	4.3	4.2	4.9	6.3	3.7	4.7
4	4.2	4.8	4.9	7.4	4.6	5.2

TABLE V
COMPARISON AMONG MODELS $C1, C2, B, S$ AND L

MAPE	Model	2007	2008	2009	2010	Average
Annual Energy	*C1*	2.5	0.9	1.0	0.8	1.3
	L	0.2	0.1	0.1	0.1	0.1
Annual Peak	*C2*	1.1	7.5	13.8	8.6	7.8
	L	0.2	2.8	2.4	7.3	3.2
Monthly Energy	*C1*	3.4	2.0	2.7	3.4	2.9
	L	1.5	1.3	1.2	2.1	1.5
Monthly Peak	*C2*	3.8	4.2	9.3	6.9	6.1
	L	2.1	3.7	3.0	4.3	3.3
Hourly Load	*B*	4.8	5.1	5.0	4.9	5.0
	S	3.5	3.9	4.0	3.6	3.8
	L	3.5	3.3	3.4	3.7	3.5

assumes end-users' behavior changes as the economic environment changes. Since a significant amount of variables are being added through the additional interaction effects, the resulting model may be over-parameterized. Depending upon the forecasting horizon and the electricity usage pattern, this approach may not provide forecast results that are as accurate as the first two options.

Table III compares the MAPE of hourly loads of the three approaches discussed above for one year ahead forecasting. The MAPE values are generated on rolling basis with a history window fixed at 3 years. Take the 3.7% under 2004 for example. We used the second approach ("divide *Load* by *GSP*") mentioned above to augment the model S_{2004} to get the model for long term forecasting, denoted as L_{2004}. The parameters are then estimated using the load, temperature, and economy data from 2001 to 2003. Based on five years of validation results, we conclude that the "replace *Trend* by *GSP*" approach on average offers the lowest MAPE (4.7%) in this case study.

B. Length of Training Data

The length of historical data for parameter estimation is another factor that impacts forecasting accuracy. Table IV lists the MAPE values generated on rolling basis with different length of history window. For example: observe 2005, with a MAPE of 7.4% in the last row. We use 4 years of history from 2001 to 2004 to estimate the parameters of the model L_{2005} (S_{2005} augmented by replacing *Trend* by *GSP*). Based on five years of validation results, we conclude that in this case study, using 2 years of historical data offers the lowest average MAPE (4.2%) for forecasting one year ahead. While this rolling simulation approach can be used for determining multiple years ahead forecasting, we may not reach the same conclusion that 2 years of historical data is optimal for 5 years ahead forecasting.

C. Comparison

We would like to compare the ex post forecasting accuracy of models $C1, C2, B, S$, and L. Some of these models ($C1, C2$, and B) already have a pre-designated variable combination, while some (S and L) require model identification. Some ($C1$ and $C2$) are based on monthly data, while some (B, S, and L) are based on hourly interval data. Due to the above characteristics, we have to apply different treatments to the models to calculate the MAPE values of ex post forecasts:

1) Classical models $C1$ and $C2$: the variables are specified in Table I, while the parameters are estimated using the eight years of historical data prior to the year to be forecasted.
2) Tao's vanilla model B : the variables are specified in Table I, while the parameters are estimated using the three years of historical data prior to the year to be forecasted.
3) Customized short term forecasting model group S: to perform ex post forecasting for the loads of year y, we cannot use the loads of year y for model building, including the tasks of parameter estimation and variable selection. To avoid using the loads of year y, we first identify the model S_{y-1}, which is selected using the year $y-1$ as the validation data and the three years $y-4$ to $y-2$ as the training data. Parameter estimation of S_{y-1} is based on the 3 years prior to year y, namely from year $y-3$ to $y-1$.
4) Customized long term forecasting model group L: similar to the analogy above, we cannot use the loads of year y to build the model when ex post forecasting the same year. Therefore, we first identify model L_{y-1}, and then estimate the parameters based on two years of historical data, $y-1$ and $y-2$.

In Table V, we list the MAPE (and absolute percentage error for annual interval summary) values of annual energy, annual peak, monthly energy, monthly peak, and hourly load from the five model groups. Table V first shows that the LTLF models (L) derived based on the proposed approach have much lower MAPE values than the classical models $C1$ and $C2$ on one year ahead ex post forecasting. On monthly energy and peak forecasting, the proposed approach reduces the MAPE by over 45%. Table V also shows that the performance of L improves on both model B and model group S.

Figs. 1 and 2 show the line plots of monthly energy and monthly peak profiles from 2007 to 2010, which confirms that the proposed approach leads to more accurate forecasts than does the counterpart.

The classical approach based on monthly data leads to significantly higher error than the proposed approach. This is because the monthly data (peak temperature, HDD, and CDD) cannot tell: 1) which hour of the day and which day of the week the high/low temperatures fall into; 2) the variation of the temperatures throughout a day; 3) the temperature profiles for modeling recency effect [1]. In addition, the HDD and CDD require the forecasters to specify the threshold or comfortable zone, which may not be very defensible.

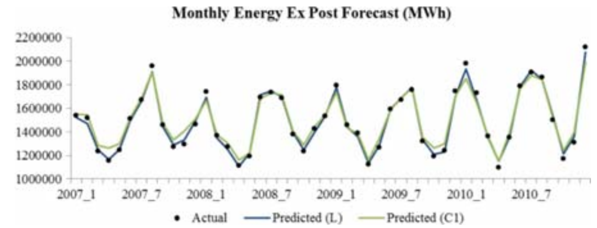

Fig. 1. Comparison on ex post forecasts of monthly energy (2007–2009).

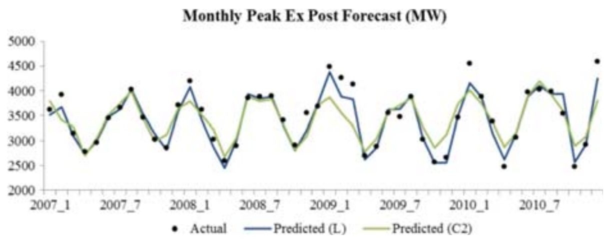

Fig. 2. Comparison on ex post forecasts of monthly peak (2007–2009).

V. Scenario Analysis

Forecasting is, by nature, a stochastic problem. Due to the uncertainty in climate and economic forecasts, long term load forecasters are encouraged to provide multiple forecasts based on different scenarios. This section discusses how to create weather and economic scenarios. Since 2011 is a year that many U.S. utilities had trouble forecasting, we use 2011 as an example to illustrate the proposed methodology.

A. Weather and Economic Scenarios

The pros and cons of several existing means to create weather scenarios have been discussed in Section II. In this paper, we use actual temperature profiles from the history to create weather scenarios. There are three components that should be clearly specified in the one year ahead load forecasting process for a given year y; or multiple years ahead load forecasting process for a given horizon starting from year y:

1) How to model the system, such as combination of weather and calendar variables, incorporation of macroeconomic indicator(s), and length of load, weather, and economy history for parameter estimation. Since the load of year y should be excluded from model building, we can use model L_{y-1}, which is identified using the most recent years of information.
2) How many years of temperature history to use. Different organizations may adopt different practices when selecting the length of temperature history, which ranges from 20 years to 50 years. NOAA, for instance, uses 30 years of history to create and update the typical meteorological year (TMY). In this paper, we also use 30 years of temperature history, from $y-30$ to $y-1$, to create 30 weather scenarios for year y. If the year y is a leap year, i.e., 2008, and the year of weather scenario is based on a non-leap year, i.e., 1991, we fill in 02/29/2008 with 02/28/1991's temperatures. If the year y is a non-leap year, i.e., 2011, and the year of weather scenario is based on a leap year, i.e., 2000, we can remove the temperatures of 02/29/2000. Based on each weather scenario, we can generate an hourly load profile for the year y using the model L_{y-1}.
3) How to extract normalized peak and energy. From each hourly load profile, we first derive monthly peak (or energy) profiles. We then find the median of the monthly peaks (or energy) for each month. The results are the normalized monthly peak (or energy) forecast. Many organizations also require the forecasts at the 10th and 90th percentiles to support the decision making processes.

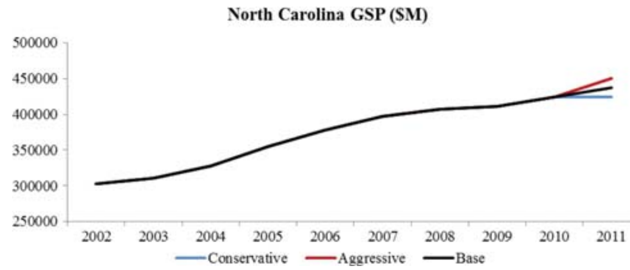

Fig. 3. History (2002–2010) and forecast (2011, 3 scenarios) of *GSP*.

Most utilities purchase economic forecasts from third parties for LTLF. The economic forecasts usually come with multiple scenarios. In this paper, we use three macroeconomic scenarios: base, aggressive, and conservative scenarios for the year of 2011 as shown in Fig. 3. For each macroeconomic scenario, we can have the same 30 weather scenarios as mentioned above. In total, we can create 90 cross scenarios.

B. Probabilistic Forecasts

Figs. 4 and 5 show one year ahead forecasting of 2011's monthly peak and energy respectively. There are 30 dashed lines representing the forecasts obtained using the 30 weather scenarios combined with the base economic scenario. In addition, we plot the 5 scenarios extracted from the 90 cross scenarios, including 10th (gray) 50th (black) and 90th (green) percentiles of the load with base economic scenario, and median load with conservative (blue) and aggressive (red) economic scenarios. The actual monthly peaks and energy of 2011 are labeled as black dots.

In practice, the 90th percentile is often used to represent a severe scenario that may happen one out of ten times. It does not mean that the load will never exceed this bound. Among the 12 monthly peaks shown in Fig. 5, the actual peak of May 2011 does exceed the 90th percentile line, which is reasonable considering the definition of the 90th percentile.

Sometimes the extreme estimates are unrealistic, because the given temperature scenario can be out of range of the training data. For instance, in Fig. 5, the extreme scenario of Jan 2011 exceeds 6000 MW, which is driven by an extremely cold year in the 1980s. Since the 90th percentile derived from the 30 scenarios is not sensitive to the extreme value, it is still reliable and practical to use such a 90th percentile curve for planning purposes.

VI. Load Normalization

Due to the variation in climate from year to year, most utilities conduct some form of weather normalization processes to esti-

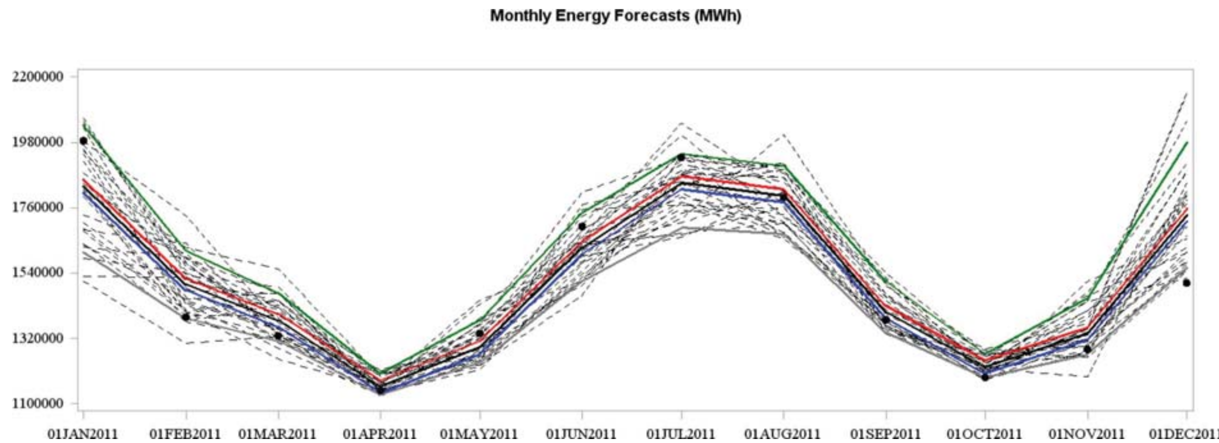

Fig. 4. Ex ante forecasts of 2011 monthly energy.

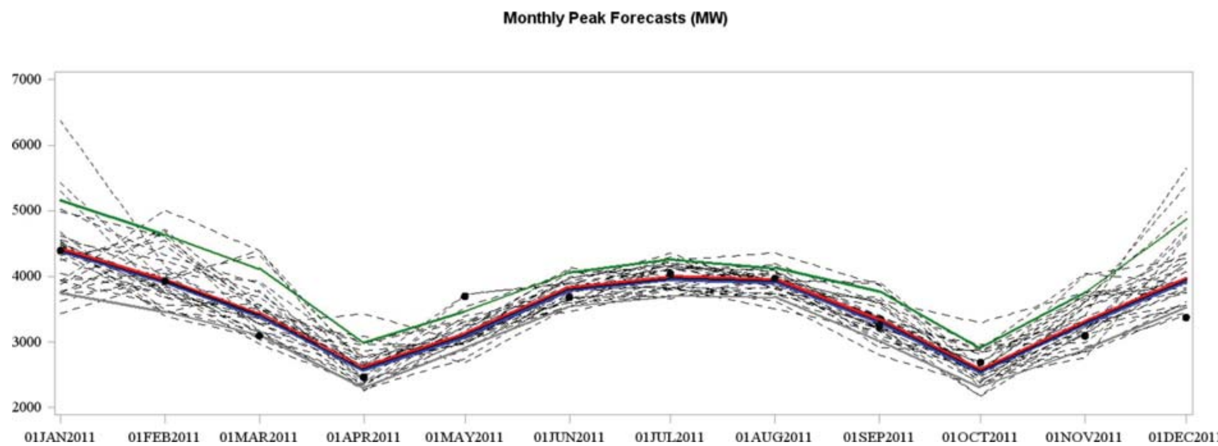

Fig. 5. Ex ante forecasts of 2011 monthly peak (30 + 5 scenarios).

mate the normalized load profile. There are two business needs for such processes: 1) understanding the load growth *without* the impact of climate change; 2) understanding the variation of the load *with* the impact of climate change. Due to the nonlinear relationship between load and weather [1], a normal weather profile usually does not lead to a normal load profile. Comparing with the conventional term *weather normalization*, a more accurate description to the process of estimating the load profile without impact of climate change should have been *load normalization against weather*.

Similar to creating weather scenarios for LTLF as discussed in Section V-A, there are three components that should be clearly specified in the load normalization process for a given year y : 1) how to model the system; 2) how many years of temperature history to use; 3) how to extract normalized peak and energy. The second and third components can be treated the same way as discussed in Section V-A, while the first one is slightly different.

When normalizing the historical load of a given year y, we should identify a model that concurrently best represents the system status in the year y, and has strong predictive power to answer the "what-if" questions. Since all the information in-

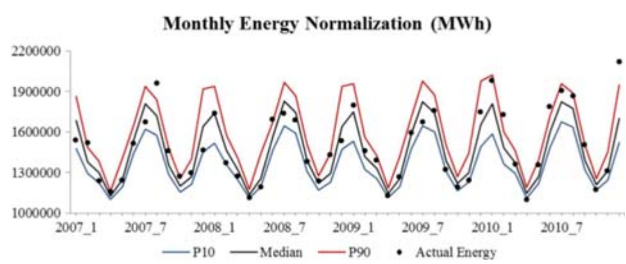

Fig. 6. Monthly energy normalization (2007–2010).

cluding load, temperature, and economy of the year y is available for load normalization, we can use the model L_y, which is identified using the data through the end of year y.

Figs. 6 and 7 present the load normalization results for monthly energy and peaks from 2007 to 2010, where the 10th percentile, median, and 90th percentile load profiles are colored in blue, black, and red respectively. The actual peaks are labeled as black dots. As shown in Fig. 6, the actual monthly energy of December 2010 is above the 90th percentile line. This is due to 3 consecutive very cold weeks, which rarely happened in the past several decades.

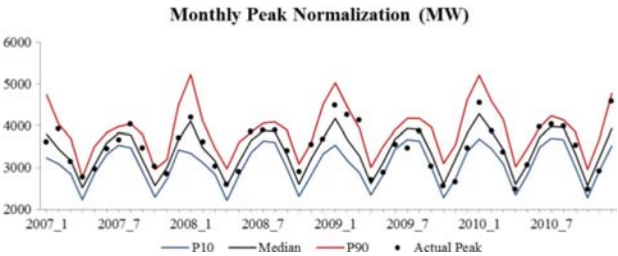

Fig. 7. Monthly peak normalization (2007–2010).

VII. Conclusion

In this paper, we presented a practical approach to LTLF. We modernized predictive modeling, weather normalization, and probabilistic forecasting with MLR models and hourly information. Through a case study at NCEMC, we showed how this method can create superior accuracy and defensibility of the forecast results over the classical approach based on monthly data. In particular, we proposed the concept of load normalization, and demonstrated a simulation approach to normalizing the load against weather.

In future work, as an expansion of the proposed methodology, we would like to further explore the following directions: 1) incorporation of high resolution spatial information; 2) how data cleansing could help improve long term load forecasts; 3) understanding how the forecast errors of explanatory variables contribute to the error of ex ante forecasts.

Acknowledgment

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References

[1] T. Hong, "Short term electric load forecasting," Ph.D. dissertation, Graduate Program of Operation Research and Dept. Electrical and Computer Engineering, North Carolina State Univ. , Raleigh, NC, USA, 2010.

[2] T. Hong, P. Wang, and H. L. Willis, "A naive multiple linear regression benchmark for short term load forecasting," in *Proc. 2011 Power Energy Soc. Gen. Meet.*, Detroit, MI, USA, Jul. 24–29, 2011.

[3] S. Fan and R. J. Hyndman, "Short-term load forecasting based on a semi-parametric additive model," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 134–141, Feb. 2012.

[4] S. Fan, K. Methaprayoon, and W. J. Lee, "Multiregion load forecasting for system with large geographical area," *IEEE Trans. Ind. Appl.*, vol. 45, no. 4, pp. 1452–1459, Jul.–Aug. 2009.

[5] S. Fan, L. Chen, and W. J. Lee, "Short-term load forecasting using comprehensive combination based on multimeteorological information," *IEEE Trans. Ind. Appl.*, vol. 45, no. 4, pp. 1460–1466, Jul.–Aug. 2009.

[6] A. Motamedi, H. Zareipour, and W. D. Rosehart, "Electricity price and demand forecasting in smart grids," *IEEE Trans. Smart Grid*, vol. 3, no. 2, pp. 664–674, Jun. 2012.

[7] N. Amjady, F. Keynia, and H. Zareipour, "Short-term load forecast of microgrids by a new bilevel prediction strategy," *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 286–294, Dec. 2010.

[8] T. Hong, "Spatial load forecasting using human machine co-construct intelligence framework," Master's thesis, Graduate Program of Operation Research and Dept. Industrial and Systems Engineering, North Carolina State Univ., Raleigh, NC, USA, 2008.

[9] T. Hong, S. M. Hsiang, and L. Xu, "Human-machine co-construct intelligence on horizon year load in long term spatial load forecasting," in *Proc. 2009 Power Energy Soc. Gen. Meet.*, Calgary, AB, Canada, Jul. 26–30, 2009.

[10] D. J. Barger, "MGE experience with INSITE spatial load forecasting," in *Proc. 2011 Power Energy Soc. Gen. Meet.*, Detroit, MI, USA, Jul. 24–29, 2011.

[11] R. J. Hyndman and S. Fan, "Density forecasting for long-term peak electricity demand," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1142–1153, May 2010.

[12] T. Hong, *Electric Load Forecasting: Fundamentals and Best Practices*. Cary, NC, USA: SAS, May 2012 [Online]. Available: http://courses.drhongtao.com/sasbelf

[13] M. Kutner, C. Nachtersheim, J. Neter, and W. Li, *Applied Linear Statistical Models*. New York: McGraw-Hill/Irwin, 2004.

[14] R. Littell, W. Stroup, and R. Freund, *SAS for Linear Models*. Cary, NC, USA: SAS, 2002.

[15] L. J. Tashman, "Out-of-sample tests of forecasting accuracy: An analysis and review," *Int. J. Forecasting*, vol. 16, no. 4, pp. 437–450, 2010.

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BEFORE THE FLORIDA PUBLIC SERVICE COMMISSION

DOCKET NOS. 20170266-EC and 20170267-EC

IN RE: PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., FOR DETERMINATION OF NEED FOR SEMINOLE COMBINED CYCLE FACILITY

IN RE: JOINT PETITION OF SEMINOLE ELECTRIC COOPERATIVE, INC., AND SHADY HILLS ENERGY CENTER, LLC., FOR DETERMINATION OF NEED FOR SHADY HILLS COMBINED CYCLE FACILITY

REBUTTAL TESTIMONY OF:

ALAN S. TAYLOR

BEFORE THE PUBLIC SERVICE COMMISSION

SEMINOLE ELECTRIC COOPERATIVE, INC.

REBUTTAL TESTIMONY OF ALAN S. TAYLOR

DOCKET NOS. 20170266-EC AND 20170267-EC

FEBRUARY 19, 2018

Q. Please state your name and address.

A. My name is Alan Taylor. My business address is 821 15th Street, Boulder, Colorado 80302.

Q. Have you previously submitted direct testimony in this proceeding?

A. Yes.

Q. What is the purpose of your rebuttal testimony?

A. The purpose of my testimony is to rebut Quantum Pasco Power, L.P.'s ("Pasco Power") witness Dr. Sotkiewicz' claims in his direct testimony that: (1) the new plants do not meet customer needs for adequate electricity at a reasonable cost because the No New Build - All-PPA Portfolio has lower CPVRRs than Seminole's proposed portfolio through 2027; and (2) the fact that Seminole's discount rate is greater than current escalation rates should cause Seminole to defer developing or acquiring new resources.

Q. What does Dr. Sotkiewicz conclude regarding comparing the CPVRRs of Seminole's proposed portfolio to the No New Build - All-PPA Portfolio?

A. Dr. Sotkiewicz concludes that the No New Build – All-PPA Portfolio represents a superior choice relative to Seminole's proposed portfolio because Seminole's evaluation results indicate that the CPVRR of the No New Build – All-PPA Portfolio is $136 million less for the initial 10-year time horizon.

Q. Do you agree with these conclusions?

A. No. First, it is important to recognize that the difference in CPVRR estimates which Dr. Sotkiewicz references is not truly a 10-year comparison. While the referenced information is for the 2018-2027 time period, Seminole issued its RFP and performed its evaluation of responses to address needs that begin in 2021. All portfolios that were evaluated were the same for the pre-2021 time period and only differed in 2021 and beyond. Seminole and Sedway Consulting both conducted a full evaluation of supply portfolios over a time period that extended 30 years, from 2021 through 2051. Thus, the 2027 date is only six or seven years into that 30-year study period and amounts to a rather near-term point of comparison.

Second, while I agree that Seminole witness Julia Diazgranados' testimony depicts the $136 million lower CPVRR estimate for the No Build Risk – All PPA Portfolio (relative to Seminole's recommended portfolio) over the initial six or seven years of the 30-year study period, I do not believe that this justifies selecting the No Build Risk – All PPA Portfolio. Incidentally, the No Build Risk - All PPA Portfolio does not include the Quantum Pasco Power facility.

Q. Is it typical to consider a 30-year planning horizon for evaluation of new generation?

A. Yes, in my experience in Florida and across the country, the evaluation of new resources is performed over the time frame of the expected life of the generation options under consideration. For new generation, that time frame is typically around 30 years. In fact, within Florida, I have provided independent evaluation services in numerous RFPs issued by Florida Power & Light, Duke Energy Florida, and Tampa Electric over the last decade, and every evaluation focused on the CPVRR of evaluated portfolios of resources over a 25-year to 35-year planning horizon in determining the least-cost plan for the utilities' customers.

Q. Seminole's analysis indicates that their recommended portfolio is $388 million less expensive on a 30-year CPVRR basis than the No Build Risk – All-PPA Portfolio. Dr. Sotkiewicz suggests that the No Build Risk – All-PPA Portfolio is better because its estimated CPVRR savings over the initial six or seven years are $136 million. Why do the results show different portfolios as being least-cost for different time horizons?

A. There are a variety of factors, but the most significant one is the simple fact that traditional revenue requirement accounting for utility- or cooperative-owned generation yields a declining stream of payments over the life of an asset, whereas most PPA pricing structures are flat or escalating over time. Because Seminole's recommended portfolio includes the SCCF that will be owned by Seminole, the declining revenue requirements associated with that resource causes the early years of total portfolio costs to be higher than portfolios that do not include that resource. However, a self-build-versus-PPA comparison of cost streams only in the initial years can yield an incomplete and incorrect conclusion about which resource is in the customers' best interests over the long term.

Q. Did Seminole's analysis also consider a shorter-term horizon?

A. Yes, and appropriately so. As the independent evaluator, I monitored and paralleled Seminole's evaluation process. The cooperative's evaluation team took numerous risks and perspectives into consideration, one of which was near-term rate impacts (i.e., near-term revenue requirements) of each evaluated portfolio. Thus, even if a portfolio's long-term 30-year CPVRR benefits advocated for it selection as a least-cost option, Seminole's evaluation team presented its Board of Trustees and executive management with near-term CPVRR information and factored that into its overall portfolio scoring process. In addition, I made presentations to the Board of Trustees where I described the general risks and benefits of short-term versus long-term transactions and PPA versus self-build resources. In the end, I believe that Seminole incorporated a great deal of information into its decision-making process, did not rely solely on the 30-year CPVRR as the portfolio selection metric, and ultimately selected a balanced portfolio that was a blend of new and existing resources in the form of PPAs and cooperative-owned assets, along with the strategic decision to remove from service of one of its coal units. I concurred that the recommended portfolio was superior to the No Build Risk – All-PPA Portfolio because the latter did not represent a balanced plan, exposed

Seminole to greater risks, and was projected to be more expensive over the long-term.

Q. In your opinion, was Seminole's analysis consistent with industry practice?

A. Yes.

Q. Regarding Dr. Sotkiewicz's conclusions about discount rates and escalation rates, please define "discount rate."

A. A discount rate is an estimated percentage rate that accounts for the time value of money and is used to present value a stream of future costs or cash flows (i.e., to put them into a single value that represents the equivalent value of those future cash flows in present terms). For electric utility power procurement analyses, I often see companies use discount rates for present value calculations that are equivalent to their costs of capital.

Q. What discount rate did Seminole use in its analysis of SCCF and SHCCF?

A. Six percent – approximately its cost of capital (i.e., its cost of debt).

Q. How does a "discount rate" compare to an "escalation rate"?

A. An escalation rate is measure of how a particular cost (e.g., facility construction cost, operating and maintenance cost) is expected to change from year to year. Escalation rates are usually close to a general inflation rate and are invariably significantly less than discount rates.

Q. Do you agree with Dr. Sotkiewicz's comparison of Seminole's discount rate to escalation rates?

A. No. Dr. Sotkiewicz states that because Seminole's discount rate (at 6%) is higher than reasonable escalation rates for combined cycle facility construction costs (in the 2.0%-2.5% range) deferring project investments will reduce CPVRR impacts. While this is mathematically true in a theoretical sense, it ignores the real world considerations that were factored into Seminole's power supply decisions. Specifically, although general inflation has been low for so long that it is tempting to view it as a permanent macroeconomic condition, there has been a great deal of monetary stimulus undertaken by the Federal Reserve and other nations' central banks over the last decade that could translate into significant price inflation for the materials and labor that go into constructing power plants. Thus, in practice, the theoretical benefits of deferring capital investment can be negated by an unexpected rise in escalation/inflation rates.

And again, aside from discount rate and escalation rate issues, Seminole's recommended portfolio is a balanced, risk-managed combination of new and existing facilities, and PPAs and self-build resources. It avoids over-reliance on out-of-peninsular-Florida resources and achieves important economic and environmental benefits associated with removing one of Seminole's coal units from service in 2023. The No Build Risk – All-PPA Portfolio does not share these desirable attributes.

Q. Does this conclude your testimony?

A. Yes.