Smart Energy Campus: A Smart Grid Test Bed for Advanced Modeling, Simulation, and Decision-Making

Xiaochen Zhang
School of Electrical and Computer Engineering
Georgia Institute of Technology
Atlanta, USA
x.zhang@gatech.edu

Santiago Grijalva
School of Electrical and Computer Engineering
Georgia Institute of Technology
Atlanta, USA
s.grijalva@ece.gatech.edu

***Abstract*—This paper presents an overview of the smart energy campus project at Georgia Tech, which uses a living smart grid test-bed covering 200 buildings with more than 400 smart meters. The test bed consists of various load components including renewable energy resources and electric vehicles. The advanced data management system is developed through a state-of-the-art IT system. A model of the distribution system is built on OpenDSS which integrates geographic information and time-variant load model. Scenario based simulations and long-term planning is studied to meet grid's future needs such as campus expansion, system renovation, shuttle electrification and energy storage. Together with the robust distribution system state estimation, the test bed allows for real-time visualization that enhances the situational awareness of the system operator, enables real-time demand response and encourages building-to-grid interactions from consumer's perspective.**

Keywords—Smart Grids; Test Bed; Renewables; Data Management; Power System Modeling; Power System Planning; Visualization.

I. Introduction

The future smart grid is believed to be a better grid which addresses the pressing environmental issues and improves the overall service quality of the entire electricity energy industry. New loads such as electric vehicles and new renewable energy technologies call for a stronger and more intelligent power system. The Georgia Tech smart energy campus test bed has been built to explore various possibilities for the future smart grid in order to achieve the social goal of economy, reliability and sustainability. The test bed seeks to improve system reliability, enhance system capacity to host renewable energy, and allow interactions between energy providers and consumers.

The smart energy campus is a living smart grid test-bed of Georgia Tech, which covers 200 buildings with more than 400 smart meters and sub-meters. It has a variety of load types including industrial load, commercial load and residential load. Solar panels and electric vehicles are also present in the test bed. The campus operational information has been recorded through advanced metering infrastructures (AMI) by a 15-minute resolution since 2012. The AMI data streaming has been integrated with research databases, facilities operational systems, and management dashboards. The research database allows investigators to perform enhanced modeling, simulation and data analytics of the electrical and non-electrical energy subsystems on campus.

In the test bed, the AMI data acquisition and management system allows high speed data transmission and enables real-time data analysis. Researchers, system operators and students could gain access to the historical and real-time database collected by AMI upon their access authority through specific API requests or web-based dashboards. Both the historical and real-time data are used to build a more accurate distribution system model, which includes a more detailed electric network model, a time-variant load model and specific models of renewables and electric vehicles. The test bed system is modeled using OpenDSS [1] and is integrated with geographic information. A robust distribution system state estimation method is used to estimate the most current system state for advanced automation functions and demand response. Time-variant load model is also developed through data mining on smart meter database, which captures the load's P-V and Q-V properties as a function of time. The test bed gathers rich information about the solar photovoltaic systems and electric vehicle charging demand. Detailed models are built for these new components to better understand the needs of the future smart grid.

Equipped with a more accurate distribution system model, facilities can make long-term planning through simulations under various scenarios. This will allow decision makers to optimize the asset management, accommodate renewable generation requirements and enable other future technologies. For the smart energy campus test bed, these long-term plans will answer the following questions:

- How to optimize existing system to accommodate future campus expansion and demand growth?
- How to perform smooth transition for campus transportation electrification?
- How to take advantage of the energy storage system for economic gains and reliability improvements?

Another goal of the test bed is to develop and test advanced tools to enhance the situational awareness of the system operators to help those making decisions for demand response and operational efficiency.

The structure of the paper is as follows. Section II introduces the AMI data acquisition and management system for the smart energy campus test bed. Section III presents the advanced modeling and state estimation based on the test bed AMI measurements. Section IV discusses the long-term planning of the test bed for the future campus needs through simulations. Section V explores the visualization functions developed for enhanced situational awareness and demand response decision-making. Section VI concludes the paper.

II. AMI Data Acquisition and Management

In the smart energy campus test bed, all buildings have extensive instrumentation for control and monitoring of electrical and mechanical signals, including approximately 400 revenue-grade smart meters. The general scheme is that a building has a main meter and may include sub-meters, typically for billable tenant load. Sometimes, meters are applied to specific areas of interest such as a chiller or PV system, or for measurement and verification (M&V) in a LEED-certified building [2]. A smart meter data management system collects and aggregates the AMI data every 15 minutes.

The real time measurements are available to users through a web-based dashboard upon authorization, see Fig. 1. Users could navigate measurements of various meters through the ION Webreach Meter Interface. As shown in Fig. 2, the interface provides detailed electricity metering records such as three phase voltage, current, power, frequency and power factor. Other key information such as solar production, water consumption and HVAC system status are also integrated in the dashboard.

Fig. 1. ION Webreach Main Menu & Building Menu [2]

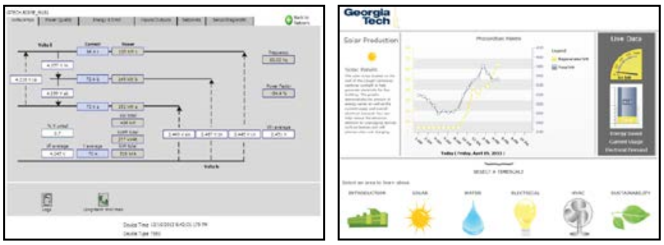

Fig. 2. ION Webreach Meter Interface [2]

The historical AMI data can be fetched and organized in a SQLite database, which is optimized for interactive visualization [3]. In Fig. 3, a Java-based "Smart Grid Plotter" serves to generate various plots according to the user's specific requirements, such as building/meter name, plot type, and studied time period.

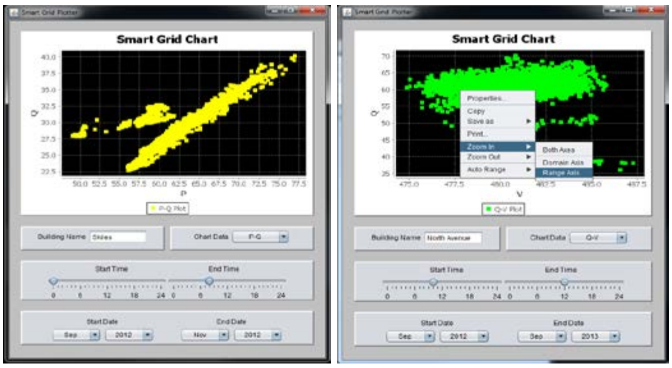

Fig. 3. Smart Grid Plotter [3]

III. Electrical Network Modeling and State Estimation

The advent of smart metering infrastructure has paved the way to enhance the accuracy of conventional distribution system models [4]. The physical and sensing test bed has been extended with a simulation environment in which the distribution systems electricity model has been further expanded and calibrated with the AMI measurements, using parametric state estimation methods. The system is modeled using Open Distribution Simulator Software (OpenDSS), an open-source comprehensive electrical power system simulation tool primary for electric utility power distribution systems [1].

A. Geographic Information Integration

In our OpenDSS model, all major system components in the test bed such as buses, transformers, feeders and loads are listed in the nomenclature and modeled with appropriate parameters. Geographic information is also integrated to the network one-line diagram. All the major components are pinned precisely on both campus maps and Google Earth, as shown in Fig. 4.

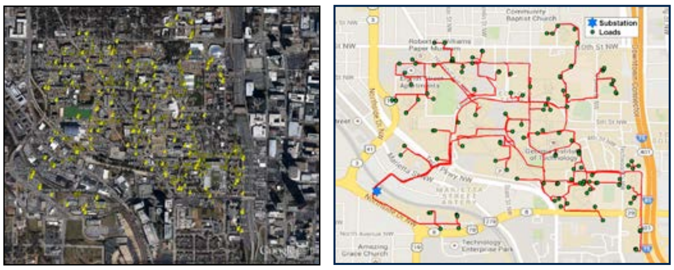

Fig. 4. Geographic Information Integration [2]

B. Distribution System State Estimation

Distribution system state estimation (DSSE) is a core function for the next generation distribution management system (DMS). Based on the real time measurements collected by the AMI, DSSE enables network operators to gain the most current system state. DSSE also facilitates advanced distribution network applications such as real-time monitoring, outage management and restoration, security assessment, energy loss optimization, and generator and load control [5].

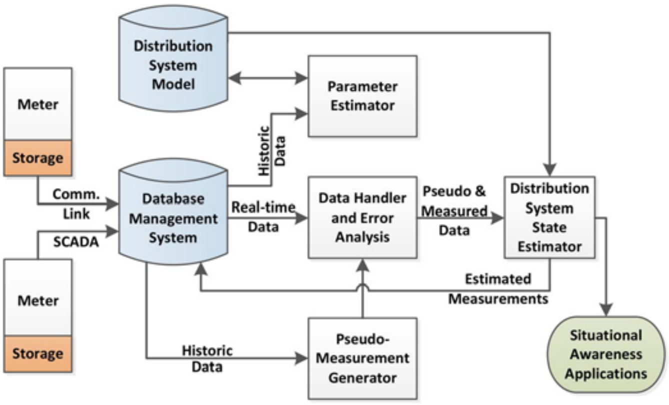

Fig. 5. Robust Distribution System State Estimation [6]

A robust distribution system state estimation for the test bed has been proposed in reference [6], as shown in Fig. 5, where a smart meter database management system is used to collect and store smart meter records through communication infrastructure. The proposed robust DSSE takes advantage of the enhanced distribution system model and cleaned data stream. The enhanced distribution system model is acquired by distribution parameter estimation. The cleaned data stream is formed on the basis of real-time AMI measurements with abnormal and missing data replaced by pseudo-measurements.

IV. LOAD MODELING

The smart energy campus test bed has a vast variety of load types from residential loads (student dorms and apartments) and commercial loads (office and instructional buildings) to industrial loads (small factories and laboratories). Solar photovoltaics (PV) are the major renewable energy resources on campus. New electric vehicle (EV) charging stations are also installed across the campus to meet the increasing charging demand of EVs on campus.

A. *Solar Photovoltaics*

The first PV array was installed at Georgia Tech in 1996 on top of the Aquatic Center, which was the largest roof-mounted PV system at the time of its construction [7]. As of 2014, there are three buildings that have PV panels on their roofs: Clough Undergraduate Learning Commons (Clough), Campus Recreation Center (CRC), and Carbon Neutral Energy Solutions Laboratory (CNES), which are shown in sequence in Fig. 6. The continuous monitoring of the PV system allows us to cumulate valuable experience and information for both PV system performance and operation.

Fig. 6. PV Systems in the Smart Energy Campus Test Bed

B. *Electric Vehicles*

As the electric vehicle (EV) is becoming a significant load component, an accurate and valid model for the EV charging demand is the key to enable accurate load forecasting, demand response, system planning, and several other important applications [8]. Since 2013, the campus test bed has seen steady growth in the number of EVs. According to a survey conducted by parking and transportation department, there are approximately 150 EVs parking on campus regularly as of Feb. 2014. Student, staff and faculty account for 26%, 32% and 42% of EV owners respectively.

To accommodate the increasing charging demand, nine dual-port Level II charging stations and three Level I charging stations are constructed in visitor-accessible locations across the campus. Fig. 7 shows the indoor and outdoor reserved parking spots for EV charging.

Fig. 7. Indoor and Outdoor Chargers

To better understand the charging behaviors of the EVs in the test bed. We proposed a statistical queuing model to simulate the EV charging demand. The proposed method adopts a data-driven non-homogeneous queue trained with the historical database of real charging measurements. Fig. 8 shows the monthly charging behavior of a specific level II charger on campus from Feb. 2014 to Feb. 2015.

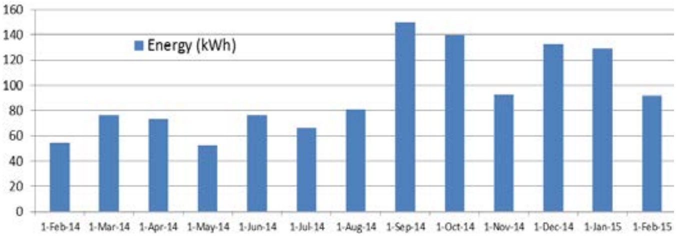

Fig. 8. Monthly Charging Consumption of a Level II Charger

C. *Time-variant load model*

From the mathematic point of view, a load model is a formula of the relationship between bus voltage and power (real and reactive) [9]. Compared with the modeling of generators and transmission systems that have been studied in detail, an accurate time-variant load model is difficult to achieve due to electricity load uncertainties and data insufficiency [10]. Traditionally, there are two popular approaches to build a load model: measurement-based approach [11, 12] and component-based approach [13, 14]. However, none of the two methods takes advantages of the immerging AMI data. In fact, the massive installation of smart meters provides two key advantages:

- The continuous monitoring capability of smart meters enables the development of a dynamic model which captures the load properties at different period of time. This is a significant leap compared with traditional static load models.
- The widespread installation of smart meters also allows estimating load model on the building level or customer level. This is the prerequisite for more advanced applications in distribution simulations and analysis.

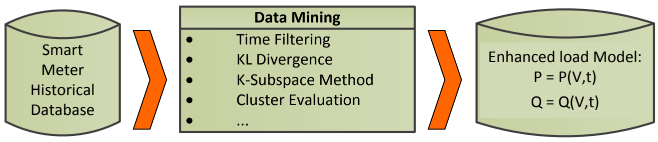

Fig. 9. A Data Driven Approach for Enhanced Load Modeling

In reference [10], we developed a data-driven approach for a time-variant load model based on the smart meter data collected from the test bed, see Fig. 9. Various machine learning algorithms are used such as data filtering, KL divergence, K-subspace method and cluster evaluation. The proposed load modeling method avoids both costly system tests in measurement-based method and extensive surveys in component-based method. Moreover the data-driven method requires no additional investments on load monitoring devices.

V. LONG TERM PLANNING

Another goal for the smart energy test bed is to understand the campus' long-term needs and help facilities make sensible decisions for far-fetched future constructions and operations in terms of system losses, future expendability, construction costs, and avoid unnecessary investment. Before the test bed model is established, facilities have limited computational resources to perform these types of tasks.

A. Future Campus Renovation and Expansion

The current test bed distribution system is designed to meet N-1 security constraints, which means if any of the feeders fails, all loads on the failed feeder will be instantly transferred to the neighboring feeder. However, as the campus load continues to grow, the abovementioned reliability criterion cannot be met without network modification. Fig. 10 shows the future campus renovations and load growth by the year of 2020.

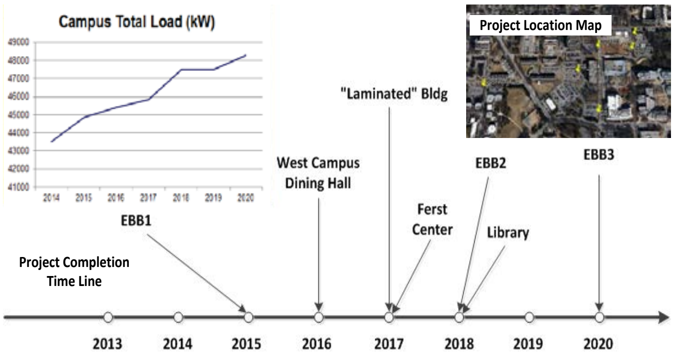

Fig. 10. Campus Long Term Planning and Load Growth Prediction

The load growth created by new buildings and renovations is estimated by current load profiles of buildings with similar function. Information such as current feeder loading condition, campus expansion location allow us to optimize which existing feeder will take the load from new buildings and decide whether building a new feeder is necessary. The test bed model serves to help facilities balancing the construction investment and system reliability. For example, a new chiller plant required to meet the increasing cooling demand may lead to one feeder fails to pass the N-1 contingency analysis. As a result, the discussing about building new feeders or sub-feeders has been brought up to the table long before the construction of the new chiller plant. Moreover, by processing all the campus load growth information together, facilities can upgrade the network "once and for all" in an optimized way which avoids repetitive constructions and waste.

B. Shuttle Electrification

Currently, there are 23 shuttle buses on campus which provide services to connect different transit hubs around the campus. It is one of our sustainable goals to replace the existing buses with electric buses. The feasibility of the program is analyzed using the smart energy campus test bed. Assume the current level of service can be maintained, two fast chargers and 10 stop chargers are needed. Given the current electric shuttle and charger price, the shuttle electrification would not guarantee economic benefits unless 56% percent of the initial investment was covered by public grants. Fig. 11 shows the cost comparison between the diesel bus system and the electric bus system in a 10 years horizon. It is clear that the electric buses require a very high initial investment but very little maintenance and operational cost. However, shuttle electrification would generate some positive externalities, such as saving 627 tons of CO_2 emissions ($22,572) annually, reduced noises and other public relations benefits ($20,014 annually).

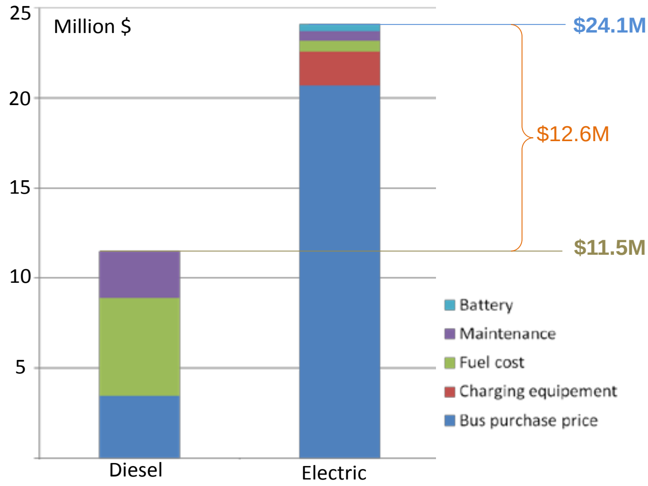

Fig. 11. Diesel & Electric Bus System Cost Comparison

C. Campus Storage

Storage has always been an ideal way to feeding power back to the grid when managing peak load and renewable energy fluctuations. Given the constraints of the test bed location and budget, battery storage is chosen as the most promising energy storage solution. By comparing the most common used Sodium-Sulfur (NaS) battery and Lithium-ion battery, we choose NaS battery due to its long term cost ($250/kWh), battery life circles (up to 13 years) and battery efficiency (78%, including power conversion efficiency). A battery control optimization algorithm has been proposed for the test bed system using Gurobi Optimizer, a commercial optimization solver for linear, quadratic and mixed integer programing problems. For a 100kWh storage system, Fig. 12 shows the best charging and discharging controls according to the real price signal of one day.

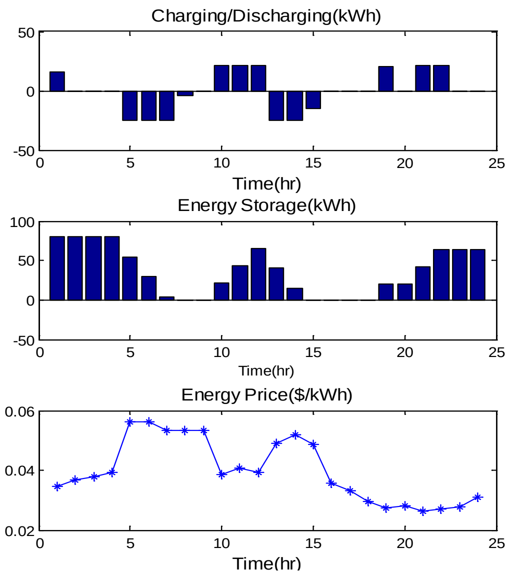

Fig. 12. Energy Storage Control According to Price Signals

VI. Situational Awareness & Demand Response

A. Enhanced Situational Awareness

Several visualization tools have been developed to present both historical data and real-time data [6]. For system operators, the visualization will allow them evaluate the real-time health of the system at a glance, which facilitates further decision-makings for system reliability. For consumers, the visualization will not only help them learn their energy consumption pattern which encourages energy conservation behaviors, but also provide a building-to-grid interface which encourages consumers' interaction with the grid. Fig. 13 left shows a web-based 3-D GUI developed by D3 visualization software, where operators could navigate the system operating states on the map. Fig. 13 right shows the energy consumption intensity of a specific building through time, where darker color means higher energy consumption.

Fig. 13. System Visualization for Enhanced Situational Awareness[6]

B. *Advanced Demand Response Strategy*

The test bed campus is served under the electric service tariff known as "Real Time Pricing – Hour Ahead Schedule" (PTR-HA) provided by Georgia Power. Customers choosing the PTR-HA tariff are notified each day of forecasted electricity prices for each hour of the following day, then prices are updated each hour, sixty minutes before becoming effective [15]. Customer baseline load (CBL) is developed for the test bed according to the energy consumption of the test bed from the previous calendar year. The total energy bill consists of two parts: the standard bill and the RTP-HA price adjustment bill, as shown in equation (1). Energy consumption under the CBL is billed under conventional tariff (standard bill). Power consumption deviated from the CBL are billed at the RTP-HA prices.

$$Total.Bill = Std.Bill + RTP.Bill \tag{1}$$

where $RTP.Bill = \sum_{hr} RTP.Price \times (Load - CBL)$.

A state-of-the-art IT system has been installed on the test bed, which allows facilities to continuously track and store real-time measurements collected by AMI. This information includes the working condition of a chiller plant and the electricity consumption over the entire campus. Therefore, system operators can vary campus energy consumption in response to RTP-HA prices. For example, system operators can reduce or delay the energy consumption by changing the chiller plant and HAVC settings during peak hours when the RTP-HA prices are high. Currently, the Metasys software is used to integrate and control chiller plant based on the RTP-HA price signal.

VII. CONCLUSION

This paper presents a smart energy campus test bed that serves to explore the needs and possibilities of the future smart grid. An advanced data management system is established to collect and process the AMI data in real-time. The physical and sensing test bed has been extended in OpenDSS in which the distribution systems electricity model has been further calibrated with the AMI measurements. Once the model was calibrated, together with an advanced load model, the simulation environment has been utilized to develop various research studies and to test various what-if scenarios for long-term system planning. Future needs such as campus expansion, system renovation, shuttle electrification and energy storage are studied using the enhanced load model and calibrated network model. A 3-D interactive visualization schema to enhance the situational awareness of the facility operators and consumers was also developed. The demand response strategy including HAVC control is realized through software in response to the RTP-HA price signal provided by utility companies.

Future development of the smart energy test bed may include deploying new components, such as voltage control devices and battery storage systems, and developing new software tools such as renewable energy controller and advanced building-to-grid optimizer.

ACKNOWLEDGMENT

The authors gratefully acknowledge the contribution of J. Peppanen on state estimation, T. Hubert on shuttle electrification, J. Grimaldo and M. Reno on OpenDSS modeling and M. Thakkar on visualization. The authors also thanks for the support of D. Chandler and S. Sywak from Facility Management, Georgia Tech.

REFERENCES

[1] Simulation Tool – Open Distribution Simulator Software (OpenDSS), available at http://smartgrid.epri.com/SimulationTool.aspx

[2] Smart Energy Campus team, "Smart Energy Campus 2013 EOY Report: A Review of 2013 Progress and Georgia Tech Smart Energy Campus Project," July 11, 2013.

[3] S. Grijalva, X. Zhang, and K. Elias, et al., "Exploiting Emerging Data for Enhanced Load Modeling," Final Report to the Power Systems Engineering Research Center (PSERC) (2014).

[4] J. Peppanen, M. J. Reno, M. Thakkar, S. Grijalva, and R. G. Harley, "Leveraging AMI Data for Distribution System Model Calibration and Situational Awareness," IEEE Transactions on Smart Grid, 2015.

[5] G. Taylor, "Report on use of distribution state estimation results for distribution network automation functions, D2.2.1," High Perform. Comput. Technol. Smart Distrib. Netw. Oper. (HiPerDNO) Res. Consortium, Brunel Univ. London, Uxbridge, U.K., Tech. Rep. FP7-248135, Apr. 2011.

[6] J. Peppanen, M. J. Reno, M. Thakkar, S. Grijalva, and R. G. Harley, "Leveraging AMI Data for Distribution System Model Calibration and Situational Awareness," IEEE Transactions on Smart Grid, 2015.

[7] Begovic, M.; Pregelj, A.; Rohatgj, A., "Four-year performance assessment of the 342 kW PV system at Georgia Tech," *Photovoltaic Specialists Conference, 2000. Conference Record of the Twenty-Eighth IEEE* , vol., no., pp.1575,1578, 2000

[8] Xiaochen Zhang; Grijalva, S., " An Advanced Data Driven Model for Residential Electric Vehicle Charging Demand," IEEE PES General Meeting, July 2015

[9] IEEE Committee, Load representation for dynamic performance analysis. IEEE Transections on Power Systems, 1993, (2),472-482.

[10] Xiaochen Zhang; Grijalva, S.; Reno, M.J., "A time-variant load model based on smart meter data mining," PES General Meeting | Conference & Exposition, 2014 IEEE , vol., no., pp.1,5, 27-31 July 2014

[11] T. Frantz, T. Gentile, S. Ihara, N. Simons, M. Waldron, "Load Behaviour Observed in LILCO and RG&E Systems", IEEE Trans., Vol. PAS-103, No. 4, April 1984.

[12] S.A.Y. Sabir, D.C Lee, "Dynamic Load Models Derived from data Acquired During System Transients," IEEE Trans., Vol. PAS-101, September 1982, pp 3365 to 3372.

[13] Vaahedi, E., et al. (1987). "Load Models for Large-Scale Stability Studies from End-User Consumption." Power Systems, IEEE Transactions on 2(4): 864-870.

[14] Price, W. W., et al. (1988). "Load modeling for power flow and transient stability computer studies." Power Systems, IEEE Transactions on 3(1): 180-187.

[15] Georgia Power, "Real Time Pricing – Hour Ahead," available at http://www.georgiapower.com/pricing/files/rates-and-schedules/ 6.30_RTP-HA-3.pdf