Minimization of Impact from Electric Vehicle Supply Equipment to the Electric Grid Using a Dynamically Controlled Battery Bank for Peak Load Shaving

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***Abstract*--This research presents a comparison of two control systems for peak load shaving using local solar power generation (i.e., photovoltaic array) and local energy storage (i.e., battery bank). The purpose is to minimize load demand of electric vehicle supply equipment (EVSE) on the electric grid. Static and dynamic control systems are compared to decrease demand from EVSE. Static control of the battery bank is based on charging and discharging to the electric grid at fixed times. Dynamic control, with 15-minute resolution, forecasts EVSE load based on data analysis of collected data. In the proposed dynamic control system, the sigmoid function is used to shave peak loads while limiting scenarios that can quickly drain the battery bank. These control systems are applied to Oak Ridge National Laboratory's (ORNL) solar-assisted electric vehicle (EV) charging stations. This installation is composed of three independently grid-tied sub-systems: (1) 25 EVSE; (2) a 47 kW photovoltaic (PV) array; and (3) a 60 kWh battery bank. The dynamic control system achieved the greatest peak load shaving, up to 34% on a cloudy day and 38% on a sunny day. The static control system was not ideal; peak load shaving was 14.6% on a cloudy day and 12.7% on a sunny day. Simulations based on ORNL data show solar-assisted EV charging stations combined with the proposed dynamic battery control system can negate up to 89% of EVSE load demand on sunny days.**

***Index Terms*—Battery Management Systems; Control System; Scheduling Algorithm; Electric Vehicles; Power System Control.**

I. Nomenclature

Abbreviations

ARRA	American Recovery and Reinvestment Act
API	Application programming interface
ω	Calibration variable for sigmoid function
c	Charge event
$E_{c,t}$	Consumed energy
i	Current
DR	Demand response
DOE	Department of Energy
ΔSOC	Difference in SOC
Δt_c	Time over which energy is consumed
DG	Distributed generation
DCS	Dynamic control system
EV	Electric vehicle
EVSE	Electric vehicle supply equipment
P_{NET}	Net power
ORNL	Oak Ridge National Laboratory
PV	Photovoltaic
P_{BB}	Power consumed/generated by battery bank
P_{EVSE}	Power consumed by EVSE
PPV	Power generated by PV array
SCS	Static control system
t_1	Start time
SOC	State-of-charge
t_2	Stop time
t	Time
t_s	Timestamp
C	Total number of charge events

II. Introduction

Oak Ridge National Laboratory (ORNL) has been awarded Department of Energy (DOE) American Recovery and Reinvestment Act (ARRA) funds to install 125 solar-assisted electric vehicle (EV) charging stations at ORNL and across Knoxville, Nashville, Chattanooga, and Memphis, TN [1]. As part of The EV Project, 25 solar-assisted charging stations have been installed at ORNL's main campus, where it has been operating since March 2011. There are three types of EVs that constitute the 21 employee owned vehicles: the Nissan LEAF (17), the Chevrolet Volt (3), and the Toyota Prius Plug-In (1). A research area being addressed in The EV Project includes understanding EV load on the electric grid and using localized remedies to decrease impact. Distributed generation (DG) technologies can be used in this regard to minimize the electrical generation requirement. DG technologies depend on energy storage and on demand schedule dispatch strategies to modulate the output of the combined system to the grid [2], [3]. These strategies address concerns of small local utility districts to mitigate spikes in power demand. This is extremely important to electric companies because mitigating power consumption allows for the current electrical infrastructure to sustain customer loads. This could help eliminate any needed upgrades if load demands were higher than what the electric grid was able to sustain thereby eliminating cost to the electric company.

The addition of EVs to the transportation sector increases the power demand from local utilities due to vehicles charging from the electric grid. This introduces a challenge to sustain system reliability which is a critical factor for the power systems industry [4]. Anticipating when and where transmission congestion and overburden will occur, and to what extent, is a complex issue. One alternative solution to this challenge is to use photovoltaic (PV) arrays (i.e., solar power) to offset electric demand and storage (e.g., battery

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bank) to minimize peak load to a level the electric company can maintain without costly upgrades to the electrical infrastructure. The utilization of solar energy and storage to solve extreme peak load periods is a promising method [5]. However, local generation and storage have challenges of their own. In particular, generated power may not be needed when produced, but rather at different times. For this reason, storage systems are needed that have the ability to provide power to the electric grid during peak demand periods.

The focus of this research paper is to minimize peak load demand on the electric grid using local power generation (e.g., solar power) and local storage (e.g., battery bank). Data being collected at ORNL through The EV Project will be used to test two control systems for peak load shaving using local power generation (47 kW PV array) and storage (60 kWh battery bank): static and dynamic. Static control of the battery bank is based on charging and discharging to the electric grid at fixed times. Dynamic control, with 15-minute resolution, forecasts electric vehicle supply equipment (EVSE) load based on data analysis of collected data. In the proposed dynamic control system, the sigmoid function is used to shave peak loads while limiting scenarios that can quickly drain the battery bank. The dynamic control system achieved the greatest peak load shaving, up to 34% on a cloudy day and 38% on a sunny day. The static control system was not ideal; peak load shaving was 14.6% on a cloudy day and 12.7% on a sunny day. Simulations based on ORNL data shows solar-assisted charging stations combined with the proposed dynamic battery control system can negate up to 89% of EVSE load demand on sunny days.

The remainder of this paper is organized as follows. Section III discusses previous research. Data analysis in Section IV reviews data that are used in this paper. Section V presents the static control system (SCS) and dynamic control system (DCS). Section VI discusses the simulation experimental setup. Results are presented in Section VII followed by the conclusion in Section VIII.

III. Previous Research

DG technologies could provide a portion of required electricity generation. Many technologies researched for DG address energy efficiency as one of the central topics. For instance, peak load shaving is used in smart homes to improve energy efficiency [6]. DG is also used for industrial sites (e.g., hospitals); using concepts of peak load shaving, thermal storage, cogeneration, and/or paralleling with the electric utility [7].

Most electricity is used during certain parts of the day. Electricity demand during peak periods can be offset, to a degree, by releasing stored energy at the appropriate times. A battery bank can be used in this regard to store energy on-site. Charging can take place during times of the day with low demand and discharging in times with high demand. ORNL uses a 47 kW PV array and a 60 kWh battery bank to mitigate peak loads caused by 25 EVSE. Two control systems are simulated and compared: a SCS and a DCS.

IV. Data Analysis

The design of the SCS and DCS for ORNL's 25 solar-assisted charging stations will be based on data collected since March 2011 from all three sub-systems: (1) 25 EVSE; (2) a 47 kW PV array; and (3) a 60 kWh battery bank. ORNL has 25 level 2 Blink EVSE (240V AC), manufactured by ECOtality. The 47 kW solar canopy is equipped with 210 Sharp ND-224UC1 modules rated at 224 W each with a 13.47% efficiency. A 50 kW inverter from PV Powered is used for DC-AC conversion. The 60 kWh battery bank uses 40-batteries from C&D Technologies, Inc. (VRS12-175F). The battery bank is discharged and charged by an SMA Technologies AG Sunny Island 5048 inverter/charger.

Data used for developing and simulating the SCS and DCS was taken from quarter 1 (January 1, 2012 through March 31, 2012). Historic data from the 25 EVSEs were collected through reporting features from Blink's website [8]. Collected variables for each charge event include: (1) connection time; (2) disconnection time; (3) start charge time; (4) end charge time; and (5) cumulative energy. Table I illustrates results from statistical analysis of this data. Fig. 1 shows a histogram for charge event start times with the mean being 10:16 AM and the distribution Gaussian in nature. The same distribution is true for connection, disconnect, total connection, charge event stop, and total charge times. This information is imperative in determining the discharge start and stop times for the SCS and forecasting usage for the DCS.

TABLE I. Quarter 1 Statistics for ORNL's EVSE

Statistics	*Value*
Average Connection Time	9:17 AM
Average Disconnect Time	4:15 PM
Average Total Connection Time	7:03
Average Charge Event Start Time	10:16 AM
Average Charge Event Stop Time	12:35 PM
Average Total Charge Time	2:23
Average Energy Consumption Per Charge	10.22 kWh

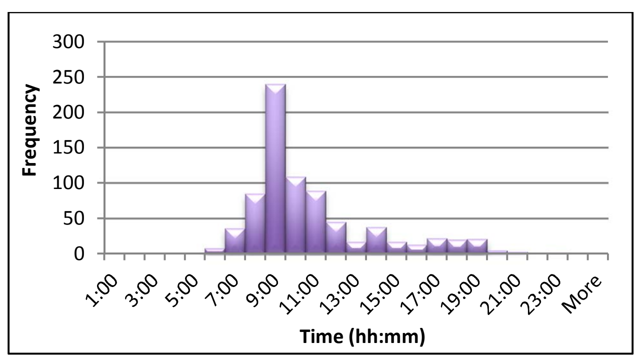

Fig. 1. Charge event start time histogram (Q1 – 2012).

Data are generated by Blink EVSE through non-instantaneous charge power events. In order to develop the SCS and DCS for peak load shaving, energy consumption through time is needed. A plot of total energy consumption in a typical month with a 15-minute resolution for the 25 EVSE is generated (Fig. 2) based on charge events. This was accomplished by using the formula:

$$E_{t,r} = \sum_{c=1}^{C} \frac{E_c * r}{\Delta t_c} \quad (1)$$

where the resolution, r, is the span of time over which data are examined, t is the instantaneous time at which the energy is consumed, $E_{t,r}$ represents the consumed energy at time t with a resolution of r, c is a charge event at time t, C is the total amount of charge events at time t, E_c is the cumulative energy of charge event c, and Δt_c is the time over which energy is consumed.

A resolution of 15-minutes was chosen for the DCS because available data from Blink and the solar inverter are updated every 15-minutes. This information is accessible through an application programming interface (API) and can be used for the DCS implementation. The maximum energy drawn within 15-minutes from the 25 EVSE is 21.875 kWh. This is calculated using the maximum output of each EVSE which is 3.3 kWh.

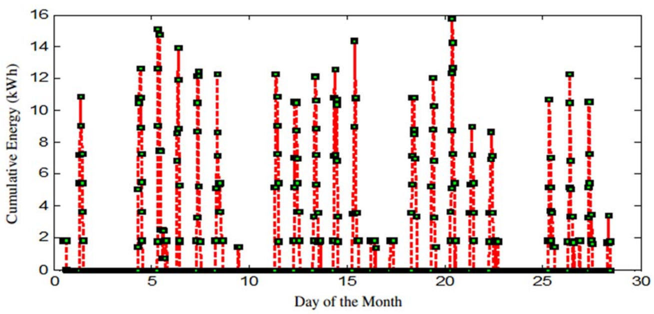

Fig. 2. A typical month of EVSE cumulative energy data with a 15-minute resolution.

V. Control System

ORNL's 25 solar-assisted charging stations (Fig. 3) consist of three independently grid-tied sub-systems: (1) 25 EVSE; (2) 47 kW PV array; and (3) 60 kWh battery bank. The total net power (P_{NET}) of this system is:

$$P_{NET} = (-P_{EVSE}) + (P_{PV}) + (\pm P_{BB}) \quad (2)$$

where P_{EVSE} represents power consumed by the EVSE and P_{BB} signifies power from charging or discharging the battery bank.

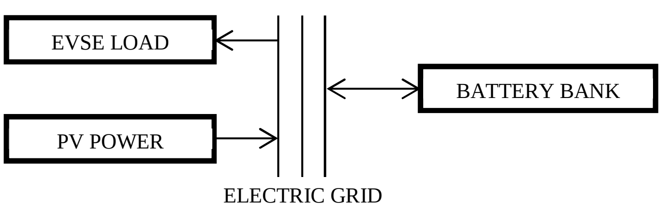

Fig. 3. General system diagram for ORNL's 25 solar-assisted charging stations.

This research compares two control systems to control the charge and discharge of the battery bank to the electric grid based on EVSE load and PV power production. The two control systems studied are: SCS and DCS.

A. Static Control System

The SCS (Figure 4) uses preset times to start (t_1) and stop (t_2) discharging of the battery bank to the grid. The process first starts with retrieving the state-of-charge (SOC) and timestamp (t_s). Based on this information, if the SOC > 50% and $t_2 \leq t_s \leq t_1$, the battery bank will discharge to the grid at current i_b. This process occurs at a set interval (e.g., every 15-minutes). Charging occurs after midnight when load on the electric grid is at a minimum.

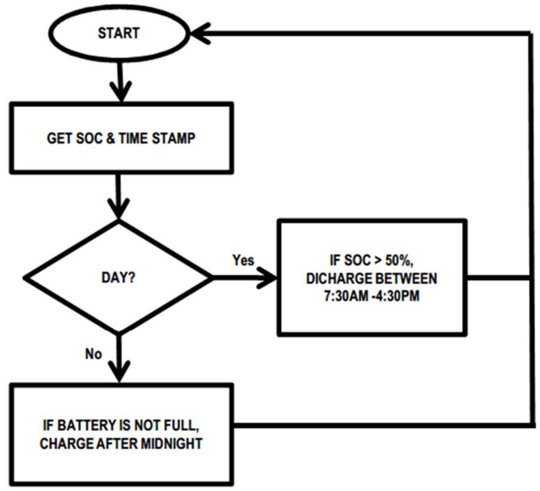

Fig. 4. Flow chart of static control system.

B. Dynamic Control System

The DCS (Fig. 5) first retrieves the total cumulative load for the EVSE, the energy production of the photovoltaic (PV) array, SOC, and timestamp (t_s). If it is after midnight and the battery bank is not fully charged, it will charge. If it is during the daytime and the EVSE load (P_{EVSE}) is greater than the power generation of the PV array (P_{PV}), the battery will discharge as long as the SOC is greater than 50%. If P_{PV} is greater than or equal to P_{EVSE}, discharging the battery bank to the electric grid is bypassed and if the battery is not full, charging will take place. This process occurs at a set interval (e.g., every 15-minutes).

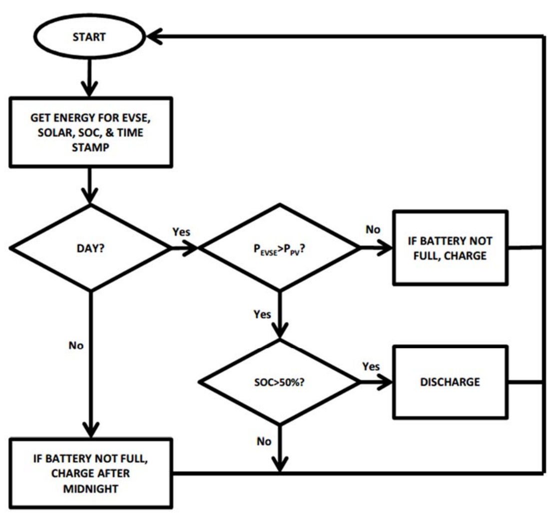

Fig. 5. Flow chart of dynamic control system.

The described DCS allows for the battery to discharge to the electric grid when the PV array is not completely negating load from the EVSE. An issue could potentially arise from this scenario if the difference between $P_{EVSE} >>> P_{PV}$. This would drain the battery bank quickly, leaving no additional energy to shave future peak loads. A mechanism is needed to control the battery's discharge rate; to ensure energy is conserved for future shaving needs. The sigmoid function is used for this purpose.

1) Sigmoid Function

The sigmoid function is a model that exhibits a progression from small to larger values that approach a climax overtime. An example application of using sigmoid functions is approximating discrete values of nerve cell activity [9]. This function is particularly useful when a detailed description is lacking.

There are two types of sigmoid functions: unipolar and bipolar. The DCS uses half of a bipolar sigmoid function to address the rise of energy demand which can quickly drain the battery. The bipolar sigmoid function (Fig. 6) refers to a special case of the function, described as:

$$f(i) = \frac{2}{1+e^{-\omega i}} - 1 \qquad (3)$$

where i represents current and ω is a calibration variable to ensure $f(i)=i$ for smaller values of i.

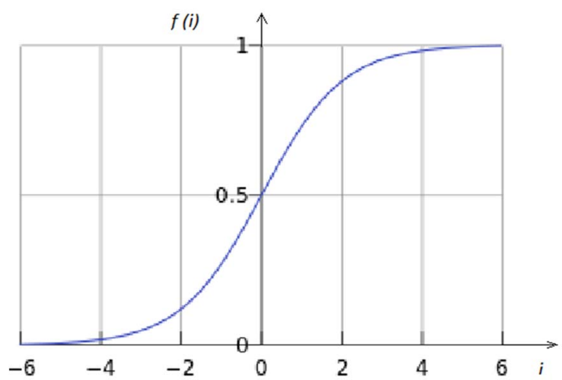

Fig. 6. A bipolar sigmoid function.

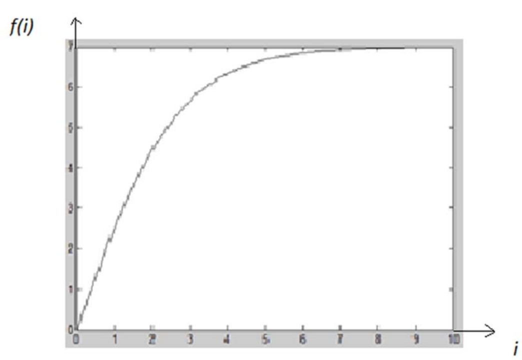

Fig. 7. A sigmoid function to limit of energy output to 7 kWh.

The shape of a sigmoid function can be modified by multipling by a factor different from 1. The shape for the DCS is determined by using the average consumption per charge, which is approximatly 10 kWh. The 60 kWh battery bank will only be discharged to 50% *SOC* to ensure the health of the batteries. This gives 30 kWh of usable energy for peak load shaving. Assuming the PV array will negate at least 30% of the average consumption per charge, that leaves 70% or 7 kWh of energy. The bipolar sigmoid function that limits the current to discharge at a maximum rate of 7 kWh is shown in Fig. 7 where ω=0.75.

C. Characteristics of Battery Bank

In order to associate the discharge rate regulated by the sigmoid function to the battery bank's characteristics, discharge and charging experiments were performed. Experiments using different discharge and charge currents were completed to determine the change in *SOC* (*ΔSOC*). Fig. 8 and 9 illustrate the battery bank's model for discharging and charging respectively.

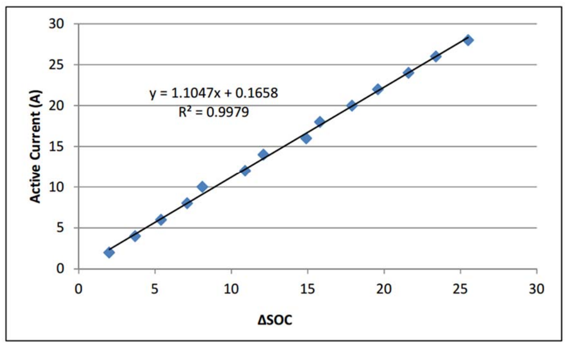

Fig. 8. The characteristic curve of the battery bank while discharging.

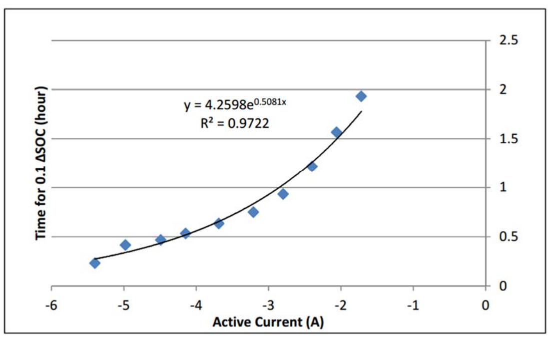

Fig. 9. The characteristic curve of the battery bank while charging.

VI. Simulation Experimental Setup

Data were taken for the 25 EVSE and PV array during quarter 1 of 2012. The initial battery bank *SOC* is assumed to be 90%. The energy consumption for each charging event is summed every 15-minutes to give the total EVSE load on the grid. A discharge start time of 7:30 and a stop time of 16:30 are chosen for the SCS. The battery's rate of discharge is set to 23A which will ensure the 60 kWh battery's *SOC* will not go below 50% for the 9 hour discharge. For the DCS, the battery's rate of discharge is dynamic, based on the difference between the total EVSE load on the electric grid and energy generated by the PV array. The battery bank is responsible for negating as much of the difference as possible. The rate of discharge is controlled by the sigmoid function where a maximum limit of 7 kWh is set.

VII. Results

DCS simulation results for a sunny day (Fig. 10) show the control algorithm reacts to the changing load as expected. The SCS results for a sunny day (Fig. 11) demonstrate static discharge between preset times. Simulations are also run for a cloudy day and very cloudy day. The DCS achieves a peak load shaving up to 34% on a cloudy day and 38% on a sunny day. The SCS only achieves peak load shaving up to 14.6% on a cloudy day and 12.7% on a sunny day. It is also shown on both figures that the extra energy generated by the PV array is supplied to the electric grid. The DCS battery bank control shaves up to 89% of the total EVSE load on a sunny day.

There are many advantages to using the DCS compared with the SCS. The battery takes the opportunity to charge during the day when solar energy is greater than the total EVSE load. This is shown in Fig. 10 where the grid with battery plot (black) is greater than the grid without battery plot (red). Both plots are equal (where time ≈ 18 hours) when the battery is full. Another advantage is the battery is discharged during times of the day when EVSE load can be shaved. This is not the case with SCS as shown in Fig. 11. The battery is constantly discharging throughout the day until the battery reaches the 50% SOC limit (where time ≈ 17 hours) and stops discharging.

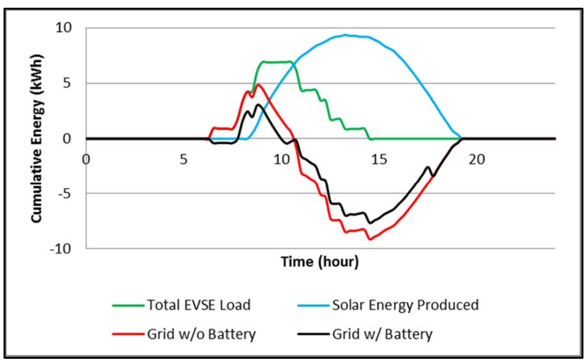

Fig. 10. Sunny day plot for DCS simulation.

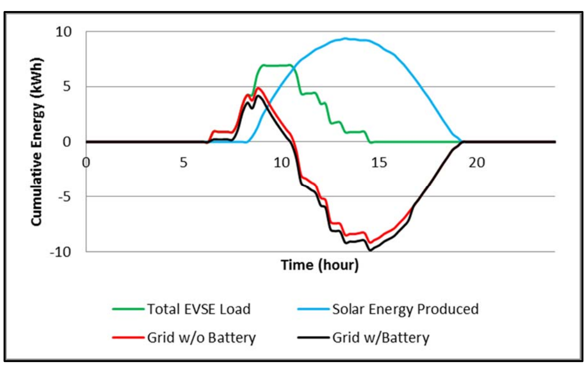

Fig. 11. Sunny day plot for SCS simulation.

VIII. Conclusion

The comparison of two control systems: dynamic (DCS) and static (SCS), for peak load shaving has been completed for 25 solar-assisted electric vehicle (EV) charging stations at Oak Ridge National Laboratory (ORNL) in Oak Ridge, TN. This installation is composed of three independently grid-tied sub-systems: (1) 25 electric vehicle supply equipment (EVSE); (2) a 47 kW photovoltaic (PV) array; and (3) a 60 kWh battery bank. The SCS discharges the battery at a static rate between preset start and stop times. The DCS discharges the battery based on the difference between the PV array and total EVSE load. The rate of discharge is controlled using the sigmoid function. Quantitatively, based on simulation results, the dynamic control system has shown to be the best option, achieving peak load shaving up to 34% on a cloudy day and 38% on a sunny day. The static control system is not ideal, only achieving peak load shaving up to 14.6% on a cloudy day and 12.7% on a sunny day. The DCS simulations also show ORNL's solar-assisted EV charging stations can provide up to 89% of the EVSE load. Future research work includes determining the optimal sizes of the PV array and battery bank for a specific amount of EVSE. Other types of DCS can also be researched.

IX. Acknowledgment

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XI. Biographies

Mekbib Tesfaye is a recent graduate of Tennessee State University (TSU), with a Master of Engineering (ME) degree (2012), from the Department of Electrical Engineering. Mekbib transferred from Addis Ababa University and received his B.S. (2008) in Electrical Engineering from TSU. Mekbib's research work includes peak load shaving and control systems for solar-assisted electric vehicle (EV) charging at Oak Ridge National Laboratory (ORNL) as part of The EV Project. Mekbib's M.E. research topic was on dog-ear detection and a notification system for a pneumatic rubber and tire manufacturing process while working for Bridgestone Tires. He has also worked on various projects such as designing a domestic and international virtual private network (VPN) and an uninterruptible solar power supply for a data center server farm and telephone systems. This work was for a federal contractor, TC Associates, which was sponsored by the Department of Energy (DOE) and National Nuclear Security Administration (NNSA) during the summer of 2011. He received an Outstanding Service Award for this work. Mekbib is also a certified Engineer in Training (EIT) for the State of Tennessee.

Charles C. Castello is an R&D Associate/Weinberg Fellow at Oak Ridge National Laboratory (ORNL) in the Whole-Building and Community Integration Research Group; part of the Energy and Transportation Science Division. Charles' current research work at ORNL is developing a control scheme for peak load shaving in an electric vehicle (EV) charging facility. This 25-station facility is part of 125 solar-assisted EV charging stations that are being built across the State of Tennessee as part of The EV Project. Charles is also assisting in data analysis associated with these stations. Other research work involves data validation for building technology sensors using statistical, filtering, and machine learning techniques. Charles received his Ph.D. in Electrical Engineering, M.S. in Computer Engineering, and B.S. in Computer Engineering from Florida International University in 2011, 2009, and 2007 respectively. His dissertation dealt with the design and development of an environmental monitoring platform.