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An Intelligent Solar-Powered Battery-Buffered EV Charging Station with Solar Electricity Forecasting and EV Charging Load Projection Functions

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***Abstract* – An intelligent energy management approach for a solar powered EV charging station with energy storage has been studied and demonstrated for a level 2 charger at the University of California-Davis West Village. The approach introduces solar PV electrical energy forecasting and EV charging demand projection to optimize the energy management of the charging station. The percentage of cloud cover is extracted from a weather forecast website for estimating the available PV electrical energy. A linear fit of the historical EV charging load from the same day of the week over the previous six weeks is employed for extracting the charging pattern of the workplace EV charging station. Both simulations and actual operation show that intelligent energy management for a charging station with a buffer battery can reduce impacts of the EV charging system on utility grids in terms of peak power demand and energy exchange, reduce grid system losses, and benefit the charging station owner through the Time-of-Use rate plans.**

Abstract –charging station; energy management; optimization; demand projection

I. INTRODUCTION

With rapid adoption of electric vehicles and mass installation of solar PV power systems, especially in high PV and EV penetration areas, electric vehicle charging, especially fast charging, and solar power availability pose a challenge for the utility grid, which lacks the capacity to deliver high power and store surplus solar electricity. It may not be economical to upgrade the distribution infrastructure in the early stage to handle this higher power demand and surplus solar energy. An approach enabling high penetration of EV charging and solar electricity into the present distribution infrastructure, while maintaining or improving PV system value, utility system reliability, and a steady power supply for EV charging during utility outages is to utilize solar powered charging stations equipped with battery storage. Very few solar powered EV charging stations with battery buffers have been demonstrated and none of them have included the effects of solar PV electricity estimation and load demand projection in their energy management strategies.

For present solar-powered charging stations with a buffer battery, the battery is always fully charged or is immediately recharged after each charging event to a fixed SOC from solar power and/or the grid in a maximum duration of several hours. The solar powered charging stations with energy storage can reduce peak power demand from the grid, but can consistently require high power to recharge them without considering solar power availability and the variability of the expected charging load demand. In the proposed energy management, instead of always keeping battery fully charged, the charge level of the buffer battery is varied according to solar PV electricity forecasting and EV charging demand projections, which can maximize usage of solar energy for EV charging and minimize impacts of solar availability and electric vehicle charging on the utility grid. This can also simplify utility grid management from the load side in the initial stages of solar PV system and EV introduction.

II. CHARGING SYSTEM DESIGN

The charging system has a 5 kW PV array, a 6.6 kW level 2 charging unit, a 35 kWh lithium iron phosphate battery pack, and a 10 kW load response bi-directional inverter, as shown in Fig. 1. The bi-directional inverter controls power flow between the different units. It has two DC ports which are connected to the PV panel and battery storage and two AC ports tied to the utility grid and EV charger, respectively. PV power can be used to charge the EV, be stored in the battery, and/or be fed to the grid. The energy stored in the battery can be used to charge an EV or fed to the grid. The PV panels, battery storage, and the grid can provide power for charging the EV.

An intelligent control system consisting of an on-site controller and a supervisory computer was introduced to communicate with the bi-directional inverter over the Modbus and the battery management system over the CANBUS. The on-site controller monitors the solar PV power, the battery status, the EV charging load, and the grid status to manage power flow between different components depending on the status of the system. Weather information from a weather forecast website is extracted to estimate the available PV electricity. Actual EV charging load data are collected and used to extract use patterns of the station for projecting the EV charging demand. Based on the estimated PV electricity and projected EV charging demand, an optimal battery SOC is calculated for charging the battery during off-peak periods if needed. Fig. 2 shows the block diagram of the control system.

Fig. 1. Charging station system

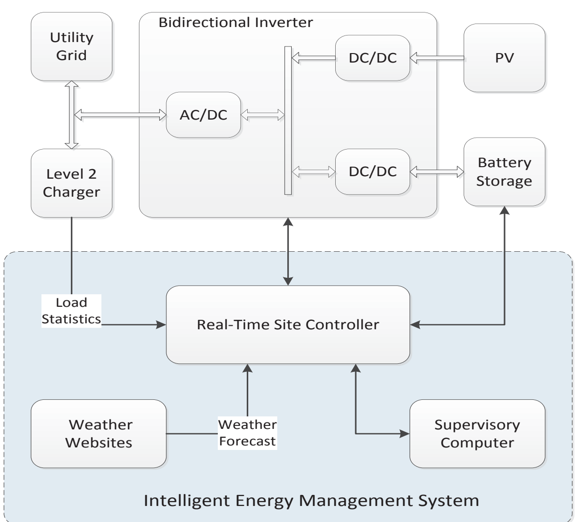


Fig. 2. Charging System Block Diagram

III. OPTIMIZATION OF ENERGY MANAGEMENT

A. Power Flow Control Strategy

The control strategy for maximizing PV energy used for EV charging and reducing grid peak power demand has been developed. According to the availability of grid power, grid-tied operating and stand-alone operating modes have been designed for the charging station. The system operating modes can be automatically switched. In the grid-tied operational mode, when an EV is plugged into the charger, PV power is used to charge the EV if it is available. If more power is needed, the remaining power is provided by the battery or/and the utility grid. If no electric vehicle is plugged-in, PV energy is stored in the battery and if the battery is completely charged, excess PV power is fed into the utility grid. During off-peak hours, grid power is used to bring the battery state-of-charge up to an optimal level if the battery charge is low. The optimal battery SOC is calculated based on the PV electricity estimation and the EV charging demand projections. Energy is never fed to the grid from the battery in the present system due to high EV charging requirements and low PV availability. In the stand-alone mode, grid power is not available. The system supplies power to charge EVs and power critical loads that cannot be supplied directly from the utility grid. Hence if PV is available, it will power the EV charger supplemented if needed by energy from the battery. If excess energy is available, the remaining PV power will be stored in the battery. By using the battery storage, the system is able to provide a reliable and constant power source from inherent intermittent solar PV power.

B. Solar PV Electricity Forecasting

Solar power forecast information is essential for efficient use and management of the solar electricity. The solar power output depends on the incoming solar insolation and the solar panel characteristics. The incoming solar insolation varies spatially and temporally. The solar insolation on the assigned solar panel for a clear sky was calculated as a function of the day of year and the time of day, multiplied by the cosine of the angle between the normal to the panel and the direction of the sun from it.

The actual solar insolation on the solar panel varies with the change of the state of the sky. Various complicated numerical weather forecast models have been developed for evaluating solar radiation for the management of the electric grid [1-3]. Solar energy forecasting for an EV charging station equipped with limited energy storage is different from that for the management of the electric grid. In this study, only the most common indicator of the state of the sky, percent cloud cover, is taken into account in calculating the solar electricity. To simplify the forecasting, the percentage of cloud cover is regarded as the percentage attenuation of solar insulation compared to that for a clear sky on the solar panel. The estimated solar PV electricity generation can be obtained by summing up the actual solar insolation over time multiplied by the panel area and the PV conversion efficiency. This is described in equation (1).

$$E_{PV}^{P} = A\eta \int (1-c)G(d,t)dt \qquad (1)$$

where E_{PV}^{P} (Wh/m^2) is the daily solar PV electricity, A (m^2) is the area of the solar panel, η is the PV panel conversion efficiency. c represents the fraction of the cloud cover, and $G(d,t)$ (W/m^2) is the solar insolation received by the PV panel on a specific day for a clear sky. $G(d,t)$ is a 2-D array, indexed by the day of the year and the time of the day.

The weather information in the XML format is obtained from OpenWeatherMap website. The weather data for every three hours in XML format is streamed and the cloud cover is extracted to predict the solar insolation.

C. EV Charging Demand Projection

EV charging load forecasting is vitally important for the economic operation and optimum control of a solar powered battery buffered EV charging station. Electric demand forecasting is mature for the electric utility industry. Various short-term, medium, and long-term load forecasting approaches have been widely used for planning and operating utility grids [4-6]. Most methods use statistical techniques based on historical data including load, weather, date, and time factors. However, EV charging as a highly variable load is dependent on driving pattern, charging habit, and time factors including the day of the week and holidays. The traditional load forecasting methods may not be suitable for forecasting EV charging load demand. It is not possible to accurately predict the EV charging events/power at a particular time, but for a community-used work place charging station, the number of EVs and the charging habit are relatively stable and average usage can be predicted. Hence the probability of EV charging and aggregated electricity demand on a certain day can be forecasted utilizing recent historical charger use data.

In order to simplify the EV charging load forecasts and to avoid the use of the unavailable information, a statistical model that determines the load model parameters from the historical use data of the latest six week period has been developed. Aggregated EV charging demand on a certain day is projected by using similar-day-of-week approach, which is based on collecting and searching historical EV charging data for the same day of the week as the forecast day. The linear fit of historical EV charging usage data using the least squares method is employed to project the charger demand for each day of the week. The general least squares method is used to fit the historical data of charge station usage to a straight line of the general form in equation (2)

$$E_{EV}^{P} = an + b \qquad (2)$$

where E_{EV}^{P} (kWh/day) is the projected EV charging load for the week n. n is an integer representing the week number in the sequence of week data for a particular day of the week. a is slope and b is intercept of the fitted model for week n=0. The values of a and b are the best fit of the historical charger use data for each day of the week using usage data for the past six weeks. The slope of the linear model reflects the trend of charging demand over the last six weeks. The projected demand for the charging station is determined by setting n=7 in the best fit equation for each day of the coming week.

D. Optimization of Battery SOC

Since most EV charging for a workplace station occurs in the relatively early morning and PV energy production is weak during this period, the available energy from the battery should be sufficient to meet the projected EV charging demand to avoid EV charging from the grid during peak hours. Hence the battery SOC to start the day should be maintained at a level dependent on the difference between the estimated PV energy generation and the projected EV charging demand for that day. If the current SOC is less than the projected SOC needed to meet the charge station demand, the battery should be charged from the grid during the off-peak hours. The targeted SOC to start the day is given by the following equation (3).

$$SOC^{P} = SOC_{mean} + \frac{k\Delta E_{ESS}^{P}}{E_{ESS}} \qquad (3)$$

$$\Delta E_{ESS}^{P} = E_{EV}^{P} - E_{PV}^{P}$$

$$\left(SOC_{max} \geq SOC^{P} \geq SOC_{min} + \frac{kE_{EV}^{P}}{E_{ESS}} \right)$$

E_{PV}^{P}: projected solar electricity (kWh) during the next day
E_{EV}^{P}: projected EV charging demand (kWh) during the next day
$\Delta E_{ESS}^{P} = E_{EV}^{P} - E_{PV}^{P}$: Projected energy deficit and surplus (positive: deploying; negative: charging)
E_{ESS}: Total battery storage capacity (kWh)
SOC_{min}: Minimum SOC (%)
SOC_{max}: Maximum SOC (%)
SOC_{mean}: Mean SOC (%) in the morning without over-night charging
SOC^{P}: Projected target of SOC to start the day
k : Correction factor to account for losses in the battery and electronics (k>1)

IV. SIMULATIONS AND SYSTEM OPERATION

A. Simulation Results

To understand the impact of the solar PV system and EV charging on utility grids, the solar PV powered EV charging systems with a buffer battery has been simulated. The PV power and the EV charging demand were constructed to represent the actual operating conditions of the present charging station, as shown in Fig. 3. The battery capacity is 35 kWh with the SOC operational window of 0.4-1.0. The PV output power through a day is represented by a sin curve between 10 am and 6 pm with the peak power of 3.6 kW. Since most EVs have either a 6.6 kW or a 3.3/3.6 kW onboard charger and EV owners charge their EVs when batteries fall to less than half their full charge, the EV charging load of 6.6 kW for 2-2.5 hours or 3.3 kW for 4 hours is used in the simulation. These input assumptions are close to the actual operating conditions of our station, which makes comparison of the simulation results with actual operation of the charging station straight-forward.

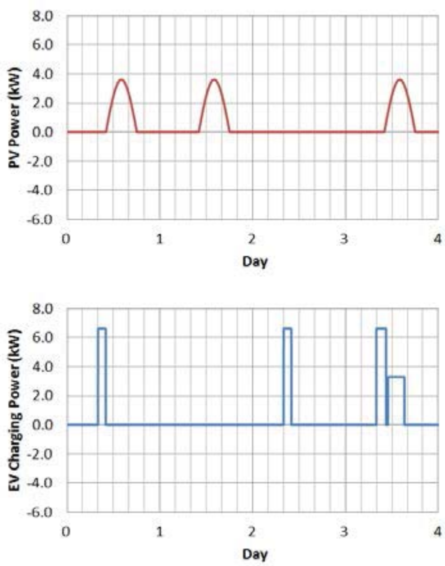


Fig. 3. Simulation inputs of PV power and EV charging load

Two energy management approaches for PV powered EV charging stations with a buffer battery have been simulated. One approach is to recharge the battery immediately to a prescribed level within 2-3 hours after each EV charging event. A charging power of 5 kW and a fixed target SOC of 0.8 are used in the simulation. The other approach is to charge the battery to the optimal SOC during off-peak hours. The optimal SOC is calculated based on PV electricity estimation and EV load projection. Charging happens during off-peak hours from midnight to 7 am. The charging power is calculated by dividing the recharge energy by the charging time. Considering the efficiency of the bi-directional inverter, a minimum charging power of 3 kW is applied. For all scenarios, the grid power and the cumulative electricity exchange between the charging system and the utility grid are plotted for evaluating the impact of various charging stations on the utility grid.

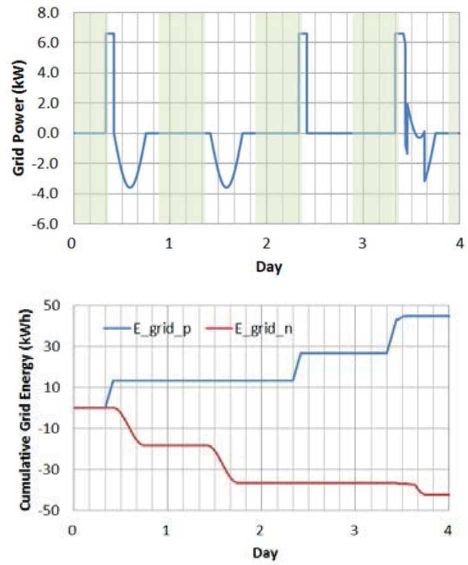


Fig. 4. PV powered EV charging station without a buffer battery

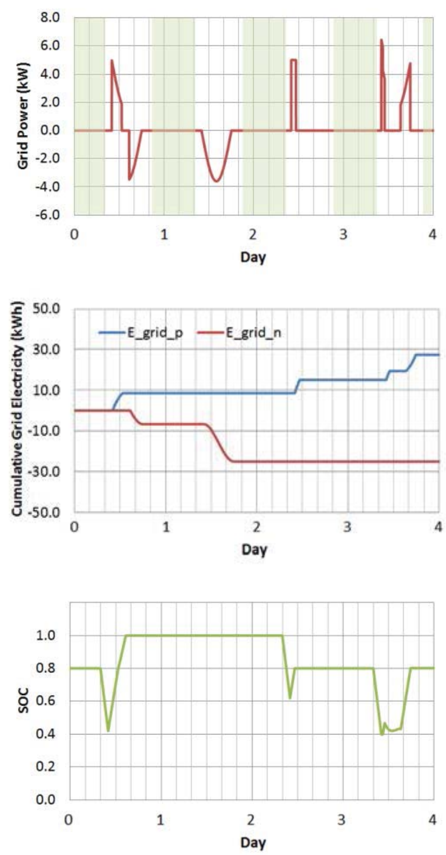


Fig. 5. Charging station with buffer battery (recharged after each charging)

Fig. 4 shows the calculated grid power and cumulative grid energy for a PV powered charging station without energy storage. The shaded areas in the grid power chart represent summer off-peak periods (9:30 pm – 8:30 am). Positive values mean power/electricity consumption from the grid and negative means power/electricity fed into the grid. The EV charging for a workplace happens in the early morning and much of the PV electricity is available in the afternoon. Hence most of the PV energy may not be directly used for EV charging.

The simulation results for a charging station with a buffer battery which is immediately recharged after each charging event has been simulated. The battery is charged up to the SOC of 0.8 after each EV charging within 2-3 hours. The simulation shows that battery recharging happens during partial-peak or on-peak periods. Compared to the PV powered charging station without energy storage, the power demand spikes from the grid were only slightly reduced. However, the energy exchange between the charging system and the utility grid was reduced by a factor of 2, as shown in Fig. 5. Considering the California average transmission and distribution losses of 5.4-6.9%, PV powered charging station with a buffer battery can significantly reduce electrical system losses.

The PV powered charging station with optimal battery SOC management was simulated using the same simulation inputs. Fig. 6 gives the simulated grid power, battery SOC, and the cumulative grid electricity. The blue dotted line represents the optimal battery target SOC, which is updated at midnight according to the simulation input. The system compares the actual battery SOC with the target SOC to decide if recharging the battery is needed during off-peak periods. Compared to the charging station without optimal battery management, the peak power demand was reduced by a factor of 2. The battery recharging power demand was shifted away from the on-peak time periods to the off-peak time periods. Since all business customers will transition eventually to time-of-use rate plans as required by the California Public Utilities Commission, the charging station with intelligent energy management will benefit from less energy use during peak periods when time-of-use rates are higher.

B. System Operation

The control and monitoring software for the charging station was developed using LabVIEW software. The software accomplishes the following four major functions: monitoring, control, protection, and optimization. The on-site controller was integrated with the charging station and used to execute the control strategy and optimize the energy storage.

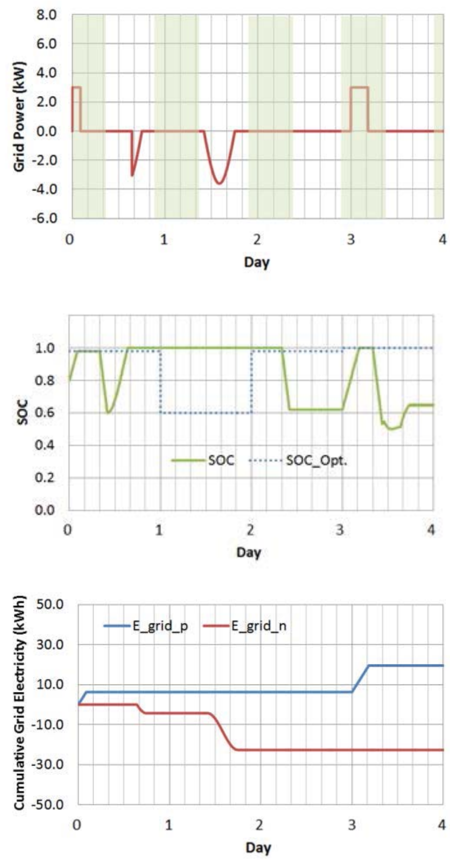


Fig. 6. Charging station with intelligent energy management

The charging station was operated for six days with the battery being recharged during off-peak time when the SOC became low. Fig. 7 shows the measured PV power and EV charging load. The actual grid power is given in Fig. 8. The grid power for the charging system without a buffer battery is calculated according to the measured PV power and charging load, and also plotted in Fig. 8 for comparison. The results show that for a workplace charging station, solar PV power cannot be directly used for EV charging and the charging station with the buffer battery can significantly reduce the peak power demand. The cumulative grid electricity is given in Fig. 9. Compared to the charging station without a buffer battery, the energy exchange between the charging system and the grid was reduced by a factor of 2.

The charging station was run continuously for a time without optimization of battery storage to collect data for the EV charging load projection. Then the intelligent energy management was activated. Fig. 10 shows the estimated PV electricity and the actual PV electricity generation. Most of the time, the estimated PV electricity is 14-17% higher than the actual PV electricity generation, which may be caused by the actual conversion efficiency of the panels being lower than claimed on their datasheet or by the hazy conditions due to forest fires nearby. On several cloudy days, the estimated PV electricity is far lower than the actual generation, which was caused by the inaccurate cloud cover information.

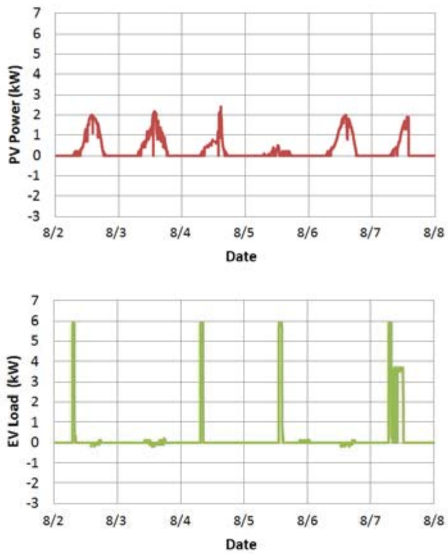
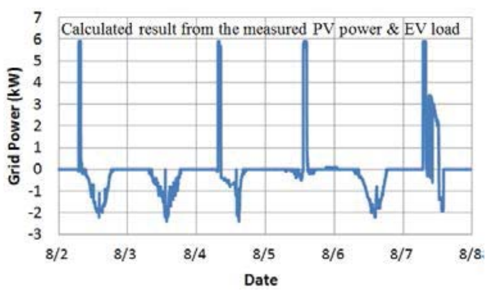
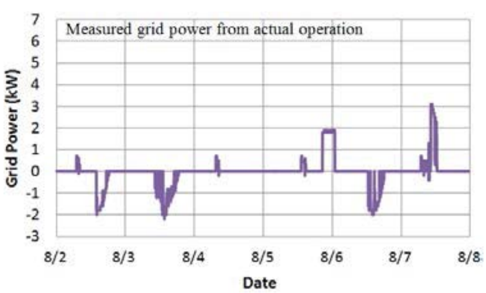


Fig. 7. Measured PV power and EV charging load



Charging station without a buffer battery



Charging station with a buffer battery

Fig. 8. Grid power for the charging system with and without a buffer battery

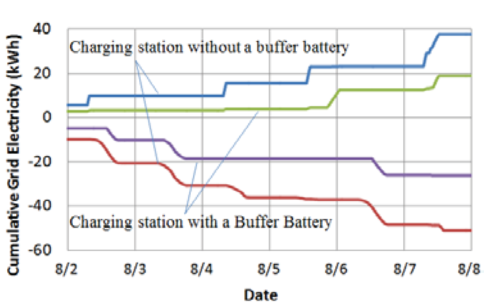


Fig. 9. Battery power and SOC and cumulative grid electricity

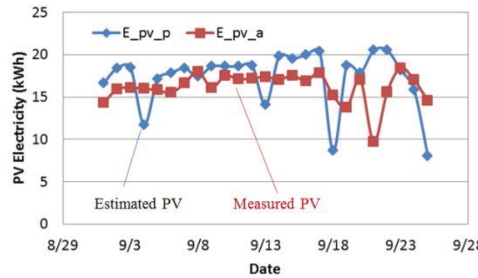


Fig. 10. Estimation of PV electricity generation

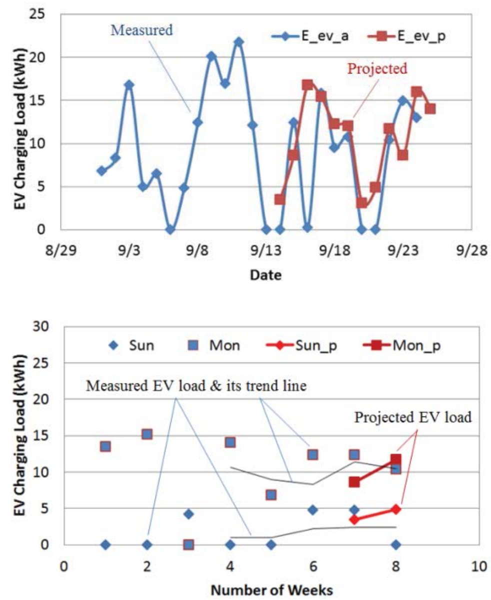


Fig. 11. EV charging load projection

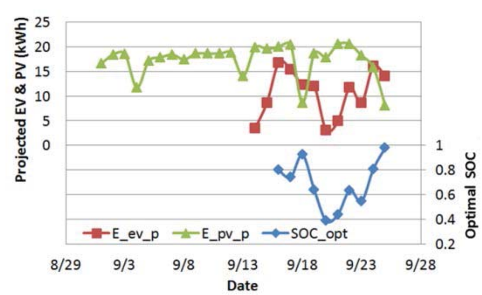


Fig. 12. Optimization of battery SOC target

The measured EV charging load and the projected load on a daily basis are plotted in Fig. 11. The projected EV charging load approximately reflects the actual charging load variation. The actual and projected load for Sunday and Monday are also given on a weekly basis in Fig. 11. The projected EV charging load approximately matched the trend lines of the actual load. Since the current charging station has only one outlet, the uncertainty and contingency will affect the result of the load demand projection.

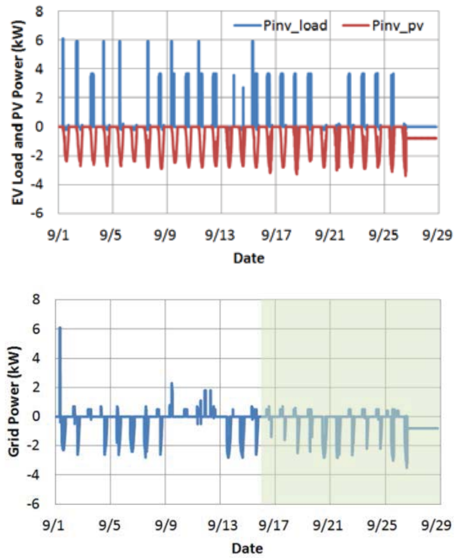


Fig. 13. Measured EV load, PV power, and grid power

The battery SOC target was optimized based on the estimated PV electricity and the projected EV charging load. The battery is recharged during off-peak time periods if the battery SOC is less than the optimal SOC target. Fig. 12 shows the estimated PV electricity, the projected EV load, and the optimized SOC target on a daily basis. The results of continuous operation are shown in Fig. 13. The charging system was activated on 9/1, the EV was charged from the grid. On 9/2 the on-site controller took control of the charging system and on 9/16 the function of optimizing energy storage was turned on. The EV charging load, the PV power, and the grid power are plotted in Fig. 12. The demonstration of the station shows the intelligent energy management can almost eliminate the charging station peak power demand for EV charging from the utility grid.

V. CONCLUSIONS

The intelligent energy management was proposed to reduce grid peak power demand and maximize PV electricity for EV charging. The battery SOC target was optimized based on the estimated PV electricity and the projected EV charging load. An on-site controller was introduced and integrated with a workplace level 2 charging station at UC Davis West Village. The control interfaces for executing the control strategy, filtering weather information, estimating PV power, projecting EV charging load, and optimizing the battery SOC were developed using LabVIEW. The charging system is routinely used by 2-3 EV users.

Both simulations and actual operation show that at a workplace charging station most of the time EV charging occurs in the early morning before solar energy is available and PV power cannot be used directly for EV charging. An EV charging station equipped with a buffer battery and with intelligent energy management can lower the station's peak power demand and reduce the energy exchange with the utility grid by a factor of 2-3. The battery recharging power demand was shifted away from the on-peak time periods to the off-peak time periods, which will benefit the charging station owner from less energy use during peak periods when time-of-use rates are higher.

The estimated PV electricity based on the extracted weather information reflects the actual PV electricity generation. More complicated PV electricity forecasting models with more accurate hour-by-hour weather information could improve the accuracy of the estimated PV electricity. The linear fit of the historical EV charging load data for each day of the week for the latest six-week period seems appropriate for extracting the charging pattern of a workplace EV charging station. Since the EV charging data from one charging outlet is contingent, charging data from multiple charging outlets will deliver high EV load prediction accuracy. The intelligent energy management strategy used in this project is best suited for charging station systems having one large energy storage battery and multiple charging outlets, such as workplace or commercial charging station systems.

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