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# Communication frame work in an electric vehicle charging station supporting solar energy management

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**ABSTRACT**

Exploiting Renewable energy to the maximum extent possible in an electric vehicle charging station (EVCS) is the key in supporting the anticipated carbon reduction from the electric vehicles (EVs). Knowing the expected load and the solar energy in advance at the EVCS can be crucial in framing a proper energy management strategy. Selection of suitable parameters associated with the participating EVs and EVCS are vital in utilizing them for predicting the probable EV load and expected solar energy for a given period under consideration. A prototype EVCS with smart communication infrastructure is developed considering solar pv as the energy source. Real time communication of the parameters between multiple agents has been established effectively using an interactive website, cloud server and an short message service (SMS) application programming interface (API). The data generated from the prototype models have been utilized in a random forest regression (RFR) classifier model in order to predict the probable solar energy and the expected EV load for every minute duration. The integrated communication frame work is found to be less complex to implement for an autonomous direct current (DC EVCS). The details provided at the graphical user interface (GUI) designed at the EVCS can be instrumental in developing a proper energy management strategy.



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## 1. INTRODUCTION

Modernisation of electric vehicle charging stations (EVCS) and the effective utilization of solar power can make the electric vehicle (EV) promotion scheme more meaningful. Autonomous microgrids are becoming more relevant in the era of artificial intelligence and machine learning. Smart communication between the charging stations and the EV users opens greater scope for learning the behaviour of multiple agents involved in the EVCS environment. Parameter identification and its timely exchange between the agents can be executed using various sensors and a suitable communication infrastructure. A detailed review is conducted in [1] on various technologies utilized for the communication towards the management of EV charging and its coordination. A reliable, high throughput, less latency communication infrastructure is required to exchange data like battery state of charge (SoC), waiting time and energy price between EVCS and EV.

The software defined network (SDN) proposed in [2] for the energy management associated with EVCS through station managenet and vehicle to grid (V2G) technology is suited for bigger vehicular networks with grid connection. The block chain technology is integrated with software-defined networking

(SDN) network in [3] to ensure security and privacy aspects of energy control in a smart grid environment involving EVs. Network function visualization (NFV) technology is combined with SDN in [4] to implement an integer linear programming to improve the utilization of renewable energy for a demand response (DR) energy management solution designed for internet of things (IoT) devices. The energy demand from smart homes are predicted by a regression tree model as reported in [5] and the deficit energy is traded with the EVs in which the hardware complexities are not considered.

Multiple machine learning models have been developed and compared in [6] to obtain an optimal coordination strategy for EVs. Battery SoC and time series load curve are used in [7], [8] not only to route the EVs towards appropriate charging stations but to suggest the type of charging also. The charging station environment discussed in [9] uses pre-defined timings with variable pricing for the charging of EVs without considering the practicality in detail. Charging demand prediction, site selection, utilization of the charger, pricing and scheduling are the key points involved in the infrastructure planning of EVCS reported in [10]. The short-term load forecasting for EVCS carried out in [10], [11] utilizes the past time series load data through different machine learning algorithms. The major input variables used in [11] are weather related data. Various applications of machine learning related to charging station utilizes the load profile of EVs [12]-[15].

Maximising the profit through optimal pricing and scheduling, utilizing various parameters like number of vehicles visited EVCS, demand response, the parking time at the station and the various pricing mechanism with reinforcement learning is proposed in [16]. A geographic specific learning is conducted recently [17] in predicting the availability of charging stations and similar inputs are used in [18] to predict the occupancy of the charging station. Consumed energy, number of charging transactions, charging time, facilities at the station, location of the station and the repeatability of the same vehicle using the same charging station have been used in [19] to predict the popularity of a given charging station. The driving distance of an EV can be estimated from the initial SoC using a model trained with the past experimental data [20]. IoT and cloud are utilized as a tool for energy management using SDN, through simulation at the consumer side [21]-[23]. Simulation studies are reported utilizing EV parameters for energy management [24]. An appropriate communication network is essential for the timely data exchange between EV sensors, EVCS and an energy control unit.

The promotion of EV schemes mainly highlighting the paradigm of carbon reduction. Solar power is a better choice for powering the EVCS and the intermittent nature of it makes the maximum utilization a challenge. Surface temperature of the PV panel and the irradiance level are the convenientt parameters in predicting the available power from a given solar PV panel. Prior arts show the importance of a reliable and suitable communication infrastructure that can be contributory to the energy management in a smaller DC EVCS network compared to the entire grid tied vehicular network of a city. The network should be easy to implement and cheaper. The proposed work focuses on the generation, communication and effective utilization of the learning parameters that can contribute to a better solar power management in an EVCS. Smart communication between the charging stations and the EV users is another aspect [25] that can be instrumental in getting various learning parameters that make the operation of EVCS more efficient.

Major contributions of the proposed work include; i) a detailed analysis of the hardware implementation of a communication infrastructure including the generation of relevant EV related parameters and appropriate communication strategies, with comprehensive hardware details; ii) a graphical user interface (GUI) which can be instrumental in framing an efficiect energy management policy at the EVCS; and iii) development of a machine learning model to predict the probable EV load and available solar energy at an EVCS utilizing the parameters made available by the communication system developed.

## 2. COMMUNICATION STRATEGIES AND HARDWARE IMPLEMENTATION

This section focuses on the possible learning parameters and the hardware enhancements made to the communication between EV user and the charging station as reported in [25]. An interactive web portal is designed wherein the operator can decide the pricing at times and the user can opt the choice. In order to generate a database that can help in predicting the expected load at the EVCS, a provision has been provided to update the generated data in a cloud server accessible to the learning agent. The data flow involves in the complete process is shown in Figure 1. Block diagram representation of the data flow is given in Figure 1(a) and a pictorial representation is given in Figure 1(b).

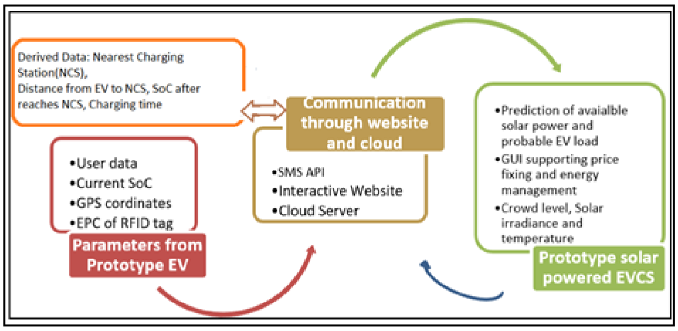
### 2.1. Generation and communication of EV related parameters

Two prototype vehicles are developed with smart communication facilities. SoC calculation is implemented using a coulomb counter module. The drainage of the battery while travelling to the charging station compared to its initial position is calculated by utilizing latitude and longitude coordinates obtained from the GPS. The well known haversine formula given in (1) is used to find the shortest distance between any two coordinates.

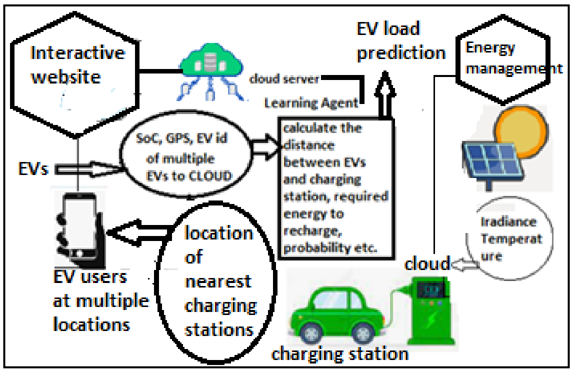
$$Distance\ between\ cordinates\ = 6371 * b\ meters \quad (1)$$

Where $b\ = 2\,\mathrm{a\,tan2}(\sqrt{a}, \sqrt{1-a})$, $a = sin^2\frac{\triangle\phi}{2} + \cos\phi_1 \cos\phi_2 sin^2\frac{\triangle\lambda}{2}$, $\triangle\,\phi$ is the difference in latitudes, $\triangle\,\lambda$ is the difference in longitudes and 6371 km is the mean radius of the earth.

All the necessary data have been communicated from charging station to the user through a short message service application programming interface (SMS API). The proposed SMS API enables the charging station to communicate bulk messages rapidly and easily through a website or application wherein the application can run on code without a cellular service or SIM card. A mobile application has been created to control the model of EV via mobile phone through a Bluetooth module which moves the prototype electric vehicle forward, left, right, or backward according to the instructions as shown in Figure 2. When the SoC level of the battery reaches a certain level an alert will be send to the registered mobile number of the EV user and a website link is provided to the user to access the details like nearest charging stations, instantaneous pricing available at each EVCS and the expected charging time. The select button of the website enables the user to select the charging station.




(a)




(b)

Figure 1. Data flow between EC and EVCS (a) block diagram represention and (b) pictorial representation

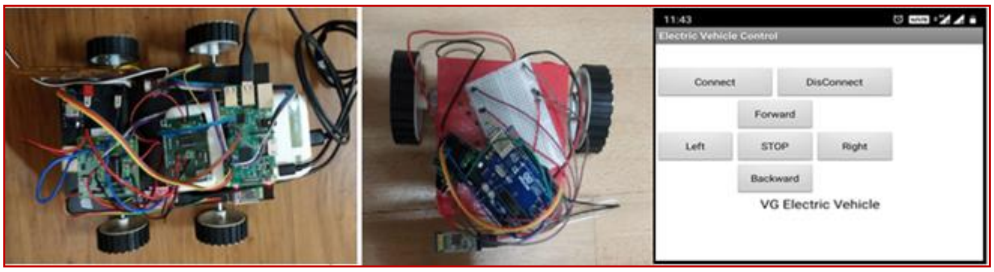



Figure 2. Prototype electric vehicles and the control knobs appeared in the mobile app

An radio frequency identification reader (RFID) receiver through RFID tag assigned to individual EV and the real time value of the crowd at the charging station are thus updated on the website. The RFID reader places the unique electronic product code (EPC) as a byte on serial transmit pin, which is used as the vehicle identifier. EV generated data are uploaded to the website through the Firebase cloud services. A Li-ion battery of 3.7 V, 4000 mAh, is connected to the Raspberry Pi along with LTC 4150 Coulomb Counter module to generate the sample SoC values. External load is used to drain the battery to test the performance of Coulomb counter and the data read by the module is pushed to the cloud server and the values are retrieved and updated on the website page. Once the current location of the EV user is updated, the coordinates are compared with all other coordinates of the EVCS and thus the nearest charging station is evaluated and displayed on the screen along with the link to the website. Provisions have been provided for the user to avail location of vehicle and SoC through the website as shown in Figure 3.

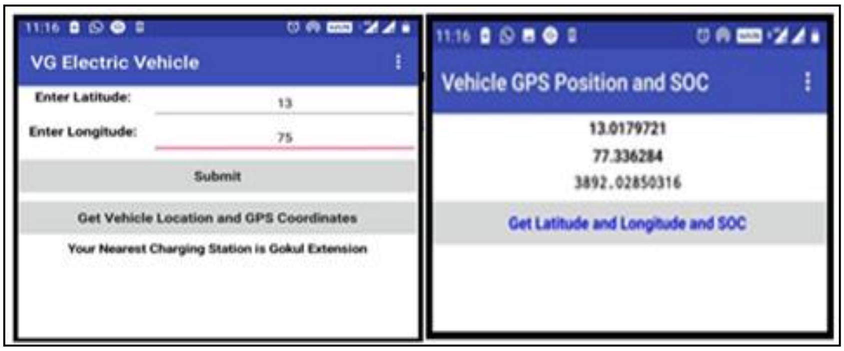



Figure 3. Screenshot of the mobile application interface

## 2.2. Development of interactive website and cloud communication

Raspberry Pi3 processor with USB boot capabilities, on-board Wi-Fi and Bluetooth has been used as the main controller for the proposed work which offers dynamic web development tools to update real time values from the station to the website. The website shows 6 different charging stations along with their cordinates, the queue and the price of electricity at the respective station. The status of the crowd and the current electricity prices for the EVCS can be updated by the concerned management through the station management page provided by the software and the updated values get reflected on the website instantaneously as shown in Figure 4.

Two sensors have been connected to a NodeMCU controller board through a multiplexer, for simultaneous acquisition of solar irradiance and surface temperature of the photovoltaic (PV) panel. A global positioning system (GPS) sensor is used to synchronize the values of irradiance and cell temperature with the corresponding time series data. The service set identifier (SSID) and the password of a Wi-Fi network is provided in the program to which the controller gets connected and transmits the data serially at a baud rate of 115200 bits per second. The real-time database of the cloud server is used to store continuous readings from the sensors. An Arduino controller is used to handle the sensor data. The irradiance and temperature data acquisition module and the uploaded data on the cloud are shown in Figure 5.


Figure 4. Screenshot of the SMS received by the user and the data on the website

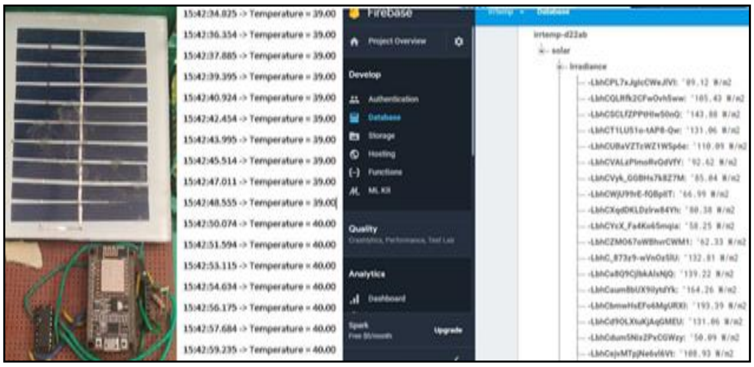


Figure 5. Data acquisition module for irradiance and temperature and the data appeared in Firebase platform

### 2.3. Prediction techniques of available solar power and expected EV load

A power prediction algorithm has been developed, which, on the basis of the irradiance and the temperature, predicts the available power with the solar module for every minute. The algorithm basically tries to predict the probable load and expected solar energy at the EVCS based on the relationship extracted among the learning parameters such as the initial state of charge of each of the vehicle battery, its distance from the charging station, the possibility that the vehicle will arrive at the charging station, the level to which it has to be charged and the price of the electricity. The information regarding the probable excess power can be vital in taking decisions related to energy management such as energy trading and energy pricing at the EVCS.

Random forest, used in the proposed algorithm for solar power predictin, is an ensemble learning method used in machine learning for classification, regression and other tasks. The irradiance and surface temperature are collected for one week using the IoT based acquisition module developed and made available to the cloud server. The time series power data is taken from the solar plant installed at the roof top of MSRIT Bangalore and the corresponding irradiance and temperature data are augmented to the database accordingly. The values of power predicted corresponding to the irradiance and temperature are tabulated, which is then send to a graphical user interface (GUI) developed at the EVCS. The values of power predicted again fed back after finding the errors and cleaning the dataset. This helps the algorithm to learn and update.

The load prediction module utilizes the current locations of the EV and the EVCS, SoC and the probability that individual EV users will arrive at a particular EVCS learnt from the past data. In order to achieve this, the data pertaining to each vehicle, its vehicle ID, SoC and their GPS coordinates are acquired from the cloud. Based on the vehicle initial SoC and the distance from the EVCS, the algorithm predicts the final SoC when they reach the charging station. The probability of a vehicle reaching the charging station is generated randomly for the ease of execution of the algorithm. The decrease in SoC per kilometer is computed, from a predefined database, after which the final state of charge is calculated.

### 2.4. Development of the GUI

A GUI is created to display the irradiance, temperature, power, the level to which the vehicle has to be charged and the predicted EV load for every minutes which help the operator at the charging station to plan the management of solar energy in advance. The module used to create a GUI is tkinter, and the programming language used is python. The purpose of storing the values in a root-node child format is to acquire them easily from the cloud to the programming platform for further analysis.

## 3. RESULTS AND DISCUSSION

The results obtained during the generation, transmission and the utilization of the identified learning parameters in an EVCS are discussed here. Charging stations can act as a data generation unit in order to utilize the renewable energy sources more efficient. Various learning parameters which can contribute to solar energy management are identified such as location details of the EVCS and EV, SoC, desired SoC, vehicle identification number, past power outputs from the solar pv, irradiance and temperature readings of the solar pv connected to the station. The irradiance and surface temperature of the solar pv collected has successfully been able to send to the Firebase cloud server along with the time series data generated from the GPS module as shown in Figure 5.

An SMS is sent automatiaclly to the registered mobile number of the user indicating the warning regarding the SoC level along with the website link. The random forest regression model is trained with a set of time series data containing available solar power, irradiance and the temperature. The plot in Figure 6 shows the correlation between the power and irradiance obtained from the plant for the same day of the prediction made. It can be observed that both the data are almost merging each other which shows the justification for selecting these parameters as the inputs for the power prediction training model.

The error metrics for the developed model have been tested with a mean square error of 36.038. The maximum permissible mean absolute error is in the range 5 to 6 and the obtained value is, well within the range. If the training was carried out with data for longer period, in which more seasonal variations would have been included, the success of prediction of power may vary since the actual power is dependent on many factors other than irradiance and temperature. Since the correlation between the power and irradince for the considered week was predominant, the prediction has been almost matching with the actual value. The mean absolute error (MAE), mean squared error (MSE) and root mean squared error (RMSE) obtained are shown in Table 1.

The website developed has been successfully able to exchange the user enties to the cloud seerver. Thus, the time required by the vehicle to reach the station is calculated along with the probable energy required to charge up to the required level in kWh. The results obtained have been made available to the GUI developed as shown in Figure 7. Table 2 concludes the various parameters collected from EV and EVCS, data derived from the basic parameters collected, modes of communication used and the utilization of derived data supporting optimal utilization of available resources.

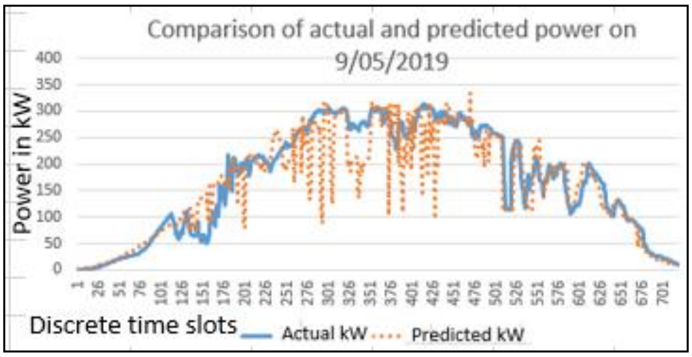
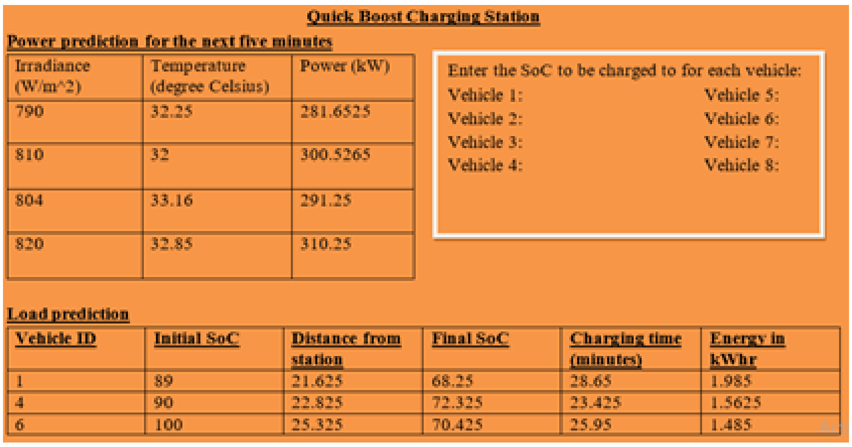



Figure 6. Comparison of actual power data from the plant and the predicted power from random forest regression (RFR) model for a day

Table 1. The value of various error metrics of the model

| Error metric | Obtained error |
|---|---|
| MAE | 4.5341548534 |
| MSE | 36.0377682846 |
| RMSE | 6.00314654848 |



Quick Boost Charging Station

Power prediction for the next five minutes

| Irradiance (W/m^2) | Temperature (degree Celsius) | Power (kW) |
|---|---|---|
| 790 | 32.25 | 281.6525 |
| 810 | 32 | 300.5265 |
| 804 | 33.16 | 291.25 |
| 820 | 32.85 | 310.25 |

Enter the SoC to be charged to for each vehicle:
Vehicle 1: Vehicle 5:
Vehicle 2: Vehicle 6:
Vehicle 3: Vehicle 7:
Vehicle 4: Vehicle 8:

Load prediction

| Vehicle ID | Initial SoC | Distance from station | Final SoC | Charging time (minutes) | Energy in kWhr |
|---|---|---|---|---|---|
| 1 | 89 | 21.625 | 68.25 | 28.65 | 1.985 |
| 4 | 90 | 22.825 | 72.325 | 23.425 | 1.5625 |
| 6 | 100 | 25.325 | 70.425 | 25.95 | 1.485 |

Figure 7. Graphical user interface (GUI) at the charging station as an energy management tool

Table 2. Data communication and its utilization

| Parameters used | Derived data | Modes of communication | Utilization |
|---|---|---|---|
| SoC, GPS coordinates, RFID tag ID | Distance between EV and EVCS, coordinates of nearest charging station, decrese in SoC per km, crowd at EVCS, probability of reaching the selected EVCS | SMS API, Website, cloud, GUI | Intimation about low SoC, routing the EV to nearest EVCS |
| Initial SoC, desired SoC, Ah and voltage of battery | Probable SoC of EV after reaches EVCS, energy required by the EV, charging time | Website, cloud, GUI | Prediction of expected load at the EVCS |
| Solar irradiance, temperature, power | Expected average solar power and energy for a given period | Cloud, GUI | Expected solar energy and probable EV load values made available to the GUI at the EVCS for energy planning |

## 4. CONCLUSION

Communication infrastructure for smart EVCS becomes complex as more and more EVs and EVCS are emerging as part of distribution grid. Autonomous DC charging stations powered with solar pv can still have the potential to manage DC loads without give back the excess solar power to the grid. A simple and unique communication system is developed and tested successfully for a solar powered EVCS supporting energy management. Multiple parameters have been identified in a solar based EVCS that can act as dynamic inputs to a power and load prediction algorithm. Prior information regarding the probable power and expected solar energy can influence the dynamic price fixing of the energy at the charging station. The total EV load at the charging station and the probable solar power during every minute have been successfully predicted by considering the identified parameters of EV and EVCS. The RFR model developed has been successfully accessed the required data and predicted the solar energy accurately. The timely exchange of the multiple generated data are tested through the cloud, interactive website and an SMS API. Finally, an interactive GUI has been provided at the EVCS which includes the predicted values of probable load and the expected solar power. The research can be extended in achieving autonomous energy management through better learning with larger data sets.

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