A Smart Solution for Fair Value Compensation (FVC) In EV-Batteries based Mobile Microgrid

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ABSTRACT

Discharging large scale of Electric Vehicle (EV) batteries when power demand is high, and charging them back when the peak is over, is relatively a new area in smart grid energy management. An Independent System Operator (ISO) will coordinate, control and monitor such operation. Since the battery lifespan is a function of number of cycles the battery is charged or discharged, the EV driver, who agrees to sign up for such a program, will need to learn about the number of cycles his EV battery is charged and discharged by the ISO to discover if incentive offered by the ISO is a fair value in contrast to the depreciation of the EV battery so caused. This paper presents a smart solution for **FAIR VALUE COMPENSATION (FVC)** in EV-batteries based mobile microgrid. The proposed architecture consists of three key functional elements: i.e.: a Cycle Counter; that will count the number of cycles the battery is charged and discharged. A Computation Logic, that will compile and present real time battery depreciation and compute fair value the EV owner deserves, decision parameters intended to help EV driver make educated decision.

Key words: Fair Value Compensation, Peak Demand Event Lithium Cobalt Oxide, Depth of Discharge.

1. INTRODUCTION

Though the primary purpose of EV battery is to supply the energy to the drivetrain, however, utilities are researching the possibility of discharging EVs for meeting peak demand [1]. Thus plugged-in EVs that commute every weekday from home to the work-place and back, can participate for peak shaving in an event of peak demand. Thus the parked and plugged-in EVs could be discharged to meet the electricity demand at peak hours and charged when the peak is over. The model will not only contribute to shave the peak, but also incentivize EV driver to receive portion of this revenue.

An Independent System Operator (ISO) is expected to materialize the above concept in the future. The ISO will coordinate, control and monitor such operation in parked and plugged-in EVs. Though the model seems promising for both, EV driver and utilities, however, state of the art, EV batteries (with Lithium Cobalt Oxide cathode and Graphite anode) has finite life. Thus the number of charge-discharge cycles impose ceiling on its durability. It is mainly because: The Lithium Cobalt Oxide cathode is designed with a particular crystal structure for stability and performance. During charge process, as indicated by the following reaction, one mole of Lithium Cobalt Oxide, that contains one mole of neutral Lithium atoms, is converted into x moles of Lithium ions releasing x moles of electrons. The resulting Lithium Cobalt Oxide Material consists of 1-x Lithium atoms. It essentially means that out of one mole of Lithium atoms, x moles of Lithium atoms are converted into Lithium ions that travel from cathode to anode.

$$LiCoO_2 \Leftrightarrow Li_{1-x}CoO_2 + xLi^+ + xe^-$$
$$xLi^+ + xe^- + 6C \Leftrightarrow Li_xC_6$$

During discharge process they return home into the cathode. Ideally they must occupy the same spot on their return in order to preserve the particular atomic structure. However, in reality it does not happen. An ion that left from spot A doesn't necessarily occupy the same spot on its return, but instead inserts herself into nearby spot B. When the ion from spot B finds her place occupied, takes up another vacant spot. Thus the crystal structure changes with (a) each charge and discharge cycle, and speed (fast charging, medium charging, and slow charging) of charging-discharging, and other factors

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eventually start to break down the particular crystal structure, and the cathode gradually loses the capacity to hold charge. A sensor can sense the voltage difference across a low value resistor between the negative terminal of the battery pack and the negative terminal of the battery ground contact.

Further Graphite anode is thermodynamically unstable in an organic electrolyte. When the battery is charged for the very first time, the graphite reacts with the electrolyte to form a porous layer called SEI (Solid Electrolyte Interphase). This reaction consumes a little lithium. SEI protects the anode from further reacting with the electrolyte. However, the SEI is an unstable protector as it protects the graphite when the battery experiences deep discharge, the SEI can partially dissolve into the electrolyte. When the battery is charged, another protective layer will form, however, the process will eat up more lithium.

In addition to the chemical reactions, that are desired to happen in the battery, there are also side reactions that generate spin-offs. These spin-offs create barriers and the ions run into roadblocks, thus contributing towards battery depreciation. Further the pure chemical crystals that form inside the cells during the charge and discharge cycles can grow large enough to put substantial mechanical pressure to internal structures inside the battery to curve the plates, swell battery casings, and short out individual cells [2].

Since batteries are usually the most expensive component of EVs, and the battery lifespan is a function of number of cycles the battery is charged or discharged, the EV driver may be either reluctant of participating in such program, or want to negotiate the revenue that could provide fair value coverage for the battery. This paper helps EV driver to compute the real time fair value the ISO owes. The proposed architecture consists of three building blocks, i.e. charge-discharge or Cycle Counter, Computation Logic, and Communication Module. These modules are explained below:

- The Cycle Counter counts the cycles and the depth of charge/discharge in each cycle. The prior art search shows Power Minder™ [3], a charge/discharge counter that provides state-of-charge information for rechargeable batteries, however, our proposed counter is completely different as it significantly enhances and builds upon the existing technology. The Cycle Counter will not only measure the state-of-charge/discharge information in one cycle, but also the number of cycles the EV battery had been charged/discharged in its entire life or in a given time period. Cycle Counter will present this data to Computation Logic.
- The Computation Logic will use this data to discover depreciation of lifespan of EV battery caused by the ISO.
- The Communication Module will convey EV driver related messages (such as battery depreciation, battery life-reduction, to GUI (Graphical User Interface); and the ISO related messages proposed in this paper (such as service authentication, service negotiation, service termination) over any state of the art communication used for V2G interface. Thus it will act as machine-to-machine communication interface, and machine-to-man communication interface.

With this system in place, the EV driver, who agrees to sign up for such a program, will be capable of discovering if the battery depreciation/lifespan-reduction caused by the ISO is counter balanced by the incentive offered by the ISO and review the contract terms and conditions for continued participation.

2. Description of Proposed System

Figure-1 shows overall concept where parked and plugged-in

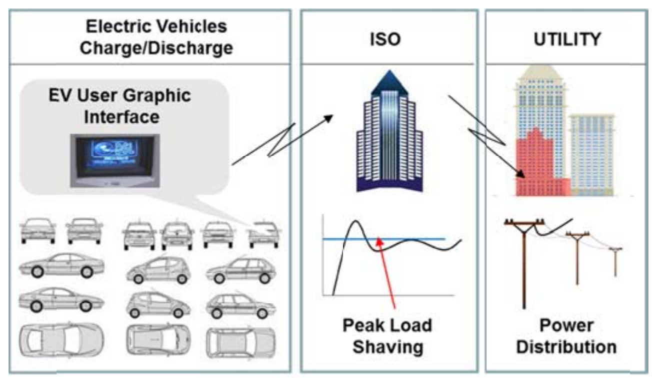

Figure 1: Concept of FVC for Automated Participation of EV in Peak Demand Shaving Event

For automated participation of EV in a peak demand event, the EV batteries can be discharged by the ISO, and charged when the peak is over. That will result in depreciation of the battery which is an asset.

The EV driver willing to contribute in peak shaving would seek fair value coverage of this asset.

Our proposed System architecture, as shown in Figure-2, will help him achieve fair value compensation. The architecture consists of three building blocks, i.e. (a) a charge discharge counter (or Cycle Counter), (b) Computation Logic, and (c) Communication Module. These modules are explained below:

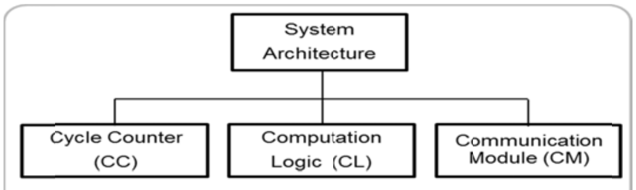

Figure 2: Building Blocks of Proposed System

2.1. Cycle Counter

The Cycle Counter is designed to (a) measure the level of initial and final charge in each individual charging incident, and the time consumed to reach that level, (b) measure the depth of discharge in each individual charging incident, and the time consumed to reach that depth, (c) total time elapsed in each charge/discharge cycle, (d) idle time (no charging or discharging activity), (e) keep log of number of cycles the EV battery had been charged and discharged in a given period of time, (f) initiate a trigger to prohibit or abort charge discharge, a Communication Module; Above noted tasks from (a) through (f) are further explained in section 2.4 titled exemplary charge/discharge model. The complete algorithm, designed for the Cycle Counter, is given in figure 3.

The algorithm in figure-3 will first decide if an EV is plugged-in to the ISO's EVSE (Electric Vehicle Service Equipment), EV driver's home EVSE or any other 3rd party public charging station. It would be decided based on the service authentication messages between EV, EVSE and the Utility Service Provider, as shown in figure 6.

2.2. Computation Logic

Computation Logic, as shown in figure 4 will make use of the knowledge gained from the Cycle Counter, to discover the number of charge discharge cycles the EV battery has gone through so far. In addition to the raw data from the Cycle Counter Computational Logic will also collect information from battery electronics (i.e. voltage drop measurement across a low-value series sensor resistor between the negative terminal of the battery and the battery pack ground contact), the EV Driver's preset preferences/policies, legacy logged and relational data, and predict remaining battery span, and also compile decision parameters intended to help EV driver. With all the collected information, Computation logic will calculate depreciation, reduction of lifespan of the EV battery caused by the ISO. It will also predict the remaining useful lifespan of the EV battery.

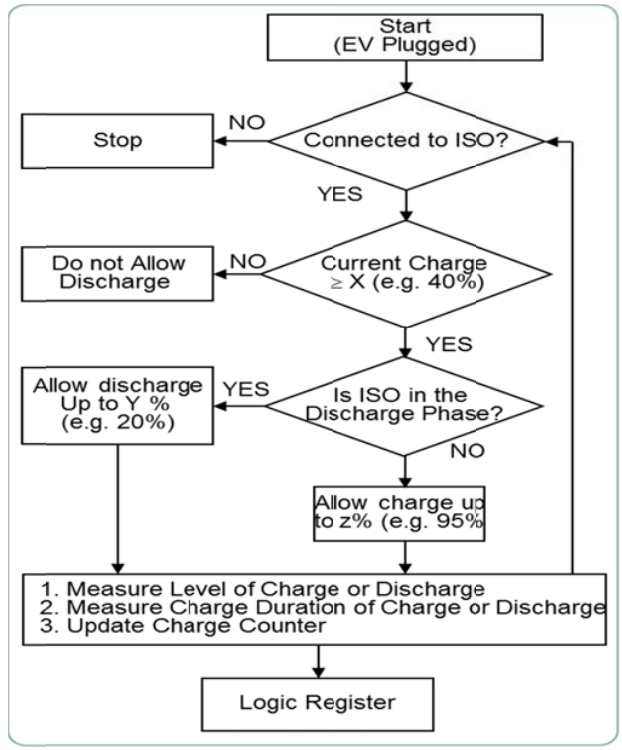

Figure 3: Cycle Counter Algorithm

ISO related information will be stored in logical register. Cycle Counter will present the data to the Computation Logic.

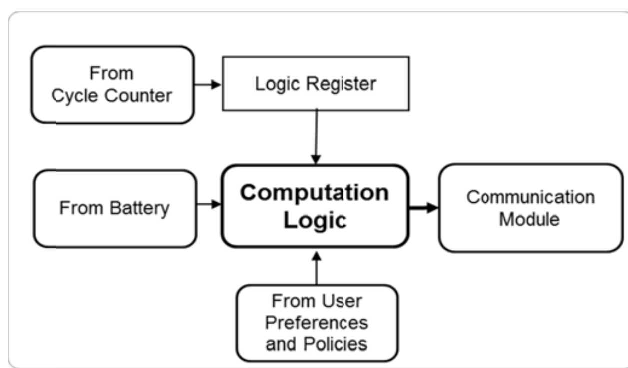

Figure 4: Blocks Diagram of Computation Logic

Our goal is to compare the real battery depreciation rate with the default depreciation rate provided by battery manufacturer to assess fair value compensation for the users participating in EV batteries-based automated peak event demand program. The default depreciation rate is usually calculated under ideal conditions, while the ISO discharging and charging procedure is always different from the ideal condition. To model the differences, we propose a new computational algorithm based on multiple, multimodal time series data mining techniques. Specifically, we model our hypotheses, i.e. "real battery depreciation is larger than default depreciation", as an event; and aim to model the probability of this event. If the probability of this event is high, it indicates that the real battery depreciation is indeed larger than the default depreciation.

In practice, we will use multiple sensors to get the measurements for each factor (such as cycle counter, voltage drop measurement, and battery pack ground contact during charging and discharging) that impacts battery lifespan. The data from each sensor can be modeled as time series data. In addition, the data from each sensor has different format. Hence, we will have to model these data as multimodal data.

In order to deal with multiple multimodal streaming data, which is usually too large to process as raw data, we need a suitable time series approximation and a feature extraction technique which can be easily deployed and is based on pattern analysis technique. We adopt SAX [4] like algorithm to the time series of each factor. SAX algorithm converts time series into a symbolic representation. Advantages of using SAX include dimensionality reduction, discretization, lower distance bounding and numerosity reduction which make it appropriate for this application. The procedure is as follows:

First the time series is normalized to remove noise, the time series of length n is divided into w equal parts and the average of each part is calculated. This is piecewise aggregate approximation (PAA) of the sequence. The cut points are determined from the Gaussian look up table. Usually the number of cut points is set as 3 and hence 4 symbols would be used for time series. Then the PAA which lies in the specified cut point slot is assigned a unique symbol or character. Thus we obtain the symbolic representation of the time series. After applying the SAX like algorithms to extract the features from multiple multimodal time series, we will employ logistic regression model [5] for predication. Based on the logistic regression, we can model the probability of the event ("real battery depreciation is larger than default depreciation") using a linear function of the predictors. In other words, the log-odds of success (the logit of the probability) is fit to the predictors using linear regression [6].

Our proposed logistic model will solve these problems: $ln[p/(1-p)] = \alpha + \beta X + e$ where p is the probability that the event Y occurs ($p(Y=1)$). Y indicates the event ("real battery depreciation is larger than default depreciation"). $p/(1-p)$ is the "odds ratio". $ln[p/(1-p)]$ is the log odds ratio. X indicates the factors that will impact the battery depreciation. Therefore, the estimated probability is $p = 1/[1 + exp(-\alpha - \beta X)]$. We will use the Maximum Likelihood Estimation (MLE) approach [7], which is a statistical method for estimating the coefficients of a model, to derive the coefficients. In the MLE approach, we employ the likelihood function (L), which measures the probability of observing the particular set of dependent variable values ($p_1, p_2, \ldots, p_n$) that occur in the sample. The likelihood function L is defined as $L = Prob\ (p_1 * p_2 * * * p_n)$. MLE involves finding the coefficients (α, β) that makes the log of the likelihood function ($LL < 0$) as large as possible. In another word, we will find the coefficients that make -2 times the log of the likelihood function ($-2LL$) as small as possible. The maximum likelihood estimates solve the following condition: $\{Y - p(Y=1)\}Xi = 0$ spread over all observations $i = 1,\ldots,n$.

2.3. Communication Module

The Communication Module, of figure 5, will handle two types of communication as shown in the application layer.

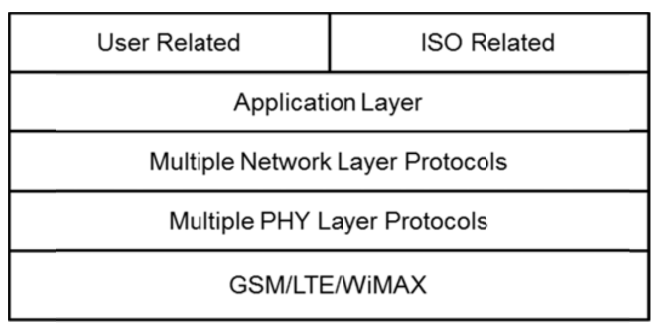

Figure 5: Communication Model

Type-1 messages are for EV driver that will convey EV driver, the battery charge/discharge/real-time depreciation message (and the depreciation translated into dollar amount) induced by ISO EVSE. The messages will be displayed on GUI (Graphical User Interface). Type-2 messages will be meant for ISO (Machine to Machine communication) that will be transmitted to, and received from ISO (such as e.g. service authentication, service negotiation, service termination, and service usage) as shown in figure 6, over any state of the art wireless communication link (such as WiMAX, LTE or GSM) used for V2G communication.

Figure 6 shows the messages between System architecture and EVSE (that may belong to ISO' home, or any other public place). These messages pertain to Service Authentication Messages, Service Negotiation Message, Service Initiation Messages, and Service Termination Messages.

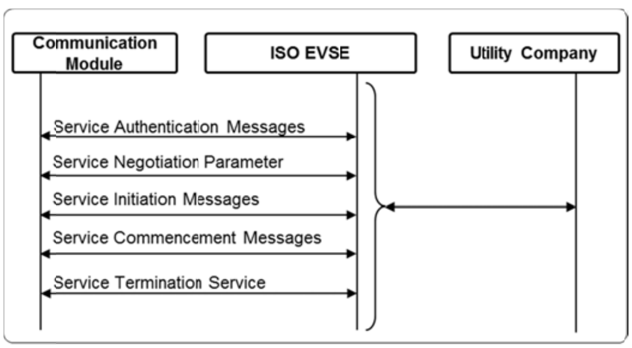

Figure 6: High Level Communication Messages

2.4. Typical Charge Discharge Model

For further explanation, we plot a model graph of Charge and Discharge against 'time' as shown in figure 7. For simplicity we assume the battery of a specific EV. The charge/discharge instances presented in the figure are explained as below:

2.4.1. Time t_0:- Let's assume that when the EV driver parks and plugs the EV in the ISO's EVSE at t0, the EV is 80% charged. The state of the charge is indicated by the line segment 'a-b' in the graph. The slope of the line segment a-b is zero that indicates that ISO is not carrying out any charge/discharges activity.

2.4.2. Time t_1 to t_2:- Let's assume that at time t_1, the utility peak occurs and ISO starts discharging the EV battery from time t_1 to t_2. This discharging event is represented by line segment b-c in the graph. The slope of the line segment b-c indicates how fast or slow ISO discharges the EV battery. The knowledge is important as it would impact the battery life. (Slow discharging will result in a longer battery life).

2.4.3. Time t_2 to t_3: Let's assume that at time t_2, the ISO stops discharging the EV battery and from time t_2 to t_3, the battery sits idle (neither charging nor discharging). This idle event is represented by line segment c-d in the graph. The length of the line segment c-d indicates how long ISO leaves the EV battery in the idle state. The knowledge is important as it would impact the battery lifespan. (Batteries should always be recharged immediately if deeply discharged. Charging batteries after each period of discharge will result in a longer battery life, as explained in section 1 Introduction).

2.4.4. Time t_3 to t_4:- Let's assume that at time t_3, the utility peak is over and the ISO starts charging the EV battery from time t_3 to t_4. This discharging event is represented by line segment d-e in the graph. The slope of the line segment d-e indicates how fast or slow ISO charges the EV battery. The knowledge is important as it would impact the battery lifespan. (Slow charging will result in a longer battery life. Also overcharging batteries will damage the battery).

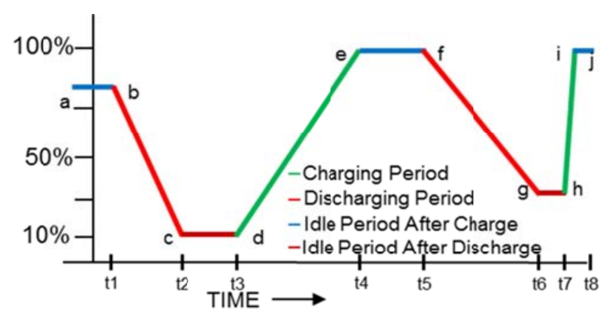

Figure 7: Model Charge Discharge Pattern

2.4.5. Time t_4 to t_5:- Let's assume that at time t_4, the ISO stops charging the EV battery and from time t_4 to t_5, the battery sits idle (neither charging nor discharging). This idle event is represented by line segment e-f in the graph. The length of the line segment e-f indicates how long ISO leaves the EV battery in the idle state. The knowledge is not important as ISO cannot be held liable for any leakages/discharges.

2.4.6. The time "t_5 to t_6", "t_6 to t_7", and "t_7 to t_8", are exact replica of event "t_1-t_2", "t_2-t_3", and t_3-t_4" correspondingly

All or any of the above information as preset by EV driver (in his preferences and policies) about the above incidents, can be communicated to the EV driver either on GUI installed in the car, or cell phone; via state of the art communication link.

3. Conclusion:

The paper presents architecture that will assist the EV drivers to discover if the battery depreciation and reduction in battery lifespan caused by an ISO is offset by the incentive offered. The model we adopted is based on the logistic regression, where we modeled the probability of the event ("real battery depreciation is larger than default depreciation") using a linear function of the predictors. Thus we computed the impact on the battery lifespan. To the best of our knowledge, our proposed system is the first to solve the fair value compensation issue for batteries based peak demand management system.

4. Future Work:

We plan to evaluate and enhance the model we developed including asset protection decision making. We also plan to include new types of detectors with better battery energy resolution. We also plan to simulate and analyze the effects of different concentrations of electrolytes and different types of cathodes such as Lithium Nickel Oxide, Lithium Manganese Oxide, Sulfur and Lithium Sulfide, which are currently under development

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