FPGA based Online Battery SOC Estimator using Weighted Mix Estimation

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Abstract: **The untimed power failure is one of major issues confronting the successful commercialization of battery powered electric cars. So, an intelligent model predictive controller which adaptively schedules the load according to the predicted remaining charge of the Electric Vehicles(EV) battery saves the energy content of the battery and ensures the safe state of the Electric Vehicle. The most important part of the model predictive controller is the accurate online estimation of the battery state of charge using an area and time efficient methodology. In this paper the authors proposes and implements an efficient yet less computationally intensive weighted mix estimation method, that combines the enhanced coulomb counting, adaptive battery model and the Open Circuit Voltage(OCV) method. The battery model parameters are tuned adaptively as the battery discharges and the tuned battery model is used by the weighted mix estimator (WME) to estimate the SOC of the battery. Due to adaptive nature of battery model used, WME serves as a robust methodology for online SOC estimation of batteries powering dynamic systems like Battery Electric Vehicles. A comparative analysis of WME has been facilitated with battery model and coulomb counting method for static and dynamic load profiles. It was found that the SOC estimated by WME was accurate and reliable, as it tracks SOC in all discharge phases of the battery under arduous conditions. Further the controller proactively optimizes the constrained battery energy by varying the power delivered to the noncritical loads and supports critical loads as per demand.**

Keywords: **FPGA, Online SOC, load scheduling, battery model, Mix estimation.**

I. Introduction

Limited energy resources in nature often require the end user to optimize the utilization of resources for achievement of goal. Battery power is a classic example of such constrained resource. So we need an efficient strategy for the proper utilization of this constrained energy source. This factor becomes more prominent in the case of electric car where the entire energy for driving is rendered from the constrained energy source namely battery.

Optimum battery management strategy is probably the most important technical step which present research of Battery powered Electric Vehicles (BEVs) lacks [1]. The primary requirement for battery management strategy is an accurate, robust and online state of charge (SOC) estimation of the battery pack in electric vehicles. Accuracy and Robustness of SOC estimation of battery is of prime importance as load in an electric vehicle is random depending on many unknown factors like surface profile, traffic conditions, driver instincts etc thus making the battery state stochastic.

Accurate online SOC estimation aids in applying proper optimization for extending the drive cycle of the electric vehicle and ensures safe and reliable journey. An imprecise SOC estimate may often affect the longevity of the battery as it leads to over/undercharging of the battery. This in turn deteriorates the performance and reliability of the of the electric vehicle battery. The SOC estimation forms the basis for extracting other parameters of the EV battery such as peak power capability, state of health and the remaining useful lifetime of the battery. The drift in the battery characteristics will create an "out of balance state" in the serially connected battery packs where accurate cell balancing maintains the lifetime of the battery pack.[2]. SOC is the basic parameter which is used in this process of cell balancing where we boost the less charged battery and buck the batteries with high SOC.

Many techniques have been developed in the past for state of charge estimation of batteries. The most commonly used are the coulomb counting method (current integration) and its enhanced variants [2]-[3].The method utilizes simple current integration for estimating the remaining charge from the nominal capacity of the battery. But the method has many presumptions like constant discharge current, controlled temperature and rated nominal capacity which seldom occurs in real world. As a result the estimated value drifts away from the real value and thus requires frequent recalibration. The dynamic electric circuit battery models such as Rint model, RC model, Thevenin's model, PNGV model and a dual polarization models [4]-[6] which simulate the real high power Li-ion battery characteristics such as electrochemical polarization, charge diffusion and concentration polarization has been proposed.But the complexity of the model increases

as the drift in battery characteristics due to aging, temperature variations and SOC variations are accounted, vice versa if the model complexity is less the accuracy is reduced drastically.

An ANN (artificial neural network) consisting of various internal nodes and layers were also used in the past for SOC estimation. A typical simple neural network consists of an input layer, a hidden layer and an output layer. Depending on the complexity of the problem the number of nodes in each layer can be adjusted. In [7] two NNs were used of which the first predicted the remaining charge and remaining time of operation in the current discharge cycle adaptively while the second NN updated the parameters due to temperature variations ,manufacturing variations, aging effects etc..

Support Vector machines (SVM) [8] for the remaining charge estimation as a kernel based method. SVM projects the original nonlinear problems in lower dimension to linear problem in higher dimension. Hansen and Wang [8] predicted the empirical SOC from current, voltage, previous SOC data and voltage fluctuation. The disadvantage of the method is the fine tuning of empirical parameters (constant C and error tube €) for accurate estimation which is time consuming.

Kalman filter and its nonlinear variants EKF and UKF[9]-[11] are a powerful tool for state estimation of the systems which requires a fairly accurate battery model and battery data feedback to "predict" and "correct" upon the current states.. An FPGA based real-time state of charge estimator is described in [12] utilizing an adaptive Kalman filter. However practical implementation of these systems in real time systems includes heavy computational overhead and huge memory requirement. This led to hybrid methods for SOC estimation which aims to improve the net accuracy by integrating the advantages of the individual estimators [11],[13]-18], use of mixed estimators [11],[13]-14], use of adaptive average estimator [15] and use of hybrid data fusion framework [16].

In this paper the authors have proposed and implemented a new SOC estimation method viz. Weighted Mix estimation (WME) which combines the open circuit voltage(OCV) method, Enhanced coulomb counting method and the adaptive battery model to estimate the online SOC of the battery accurately. The proposed estimation technique improves the estimation accuracy of the enhanced coulomb counter designed by the authors in [2] with minimal area and time complexity. Subsequently a model predictive controller based on WME is implemented which dynamically allocates the load according to the predicted SOC data.

The highly fluctuating load profiles demands for fast and concurrent computational capabilities thus making FPGAs the prime contender [19]-[20]. The implementation of such controller for dynamic power management using a microcontroller or microprocessor is not suitable in case of electric cars as high-speed data acquisition and processing is the basic requirement of the system. FPGA and Application Specific Integrated Circuits (ASIC) are possible solutions to fulfill the hardware requirements for implementation of such control strategy. A wide variety of custom made FPGA development boards specifically designed for automobile applications from Xilinx and Altera helps in fast reconfiguration of logic design and reduces the time to market.

The paper is organized as follows Section 2 explains the experimental setup. Section 3 gives detailed description of enhanced coulomb counting method. In Section 4 dynamic battery modeling and parameter estimation has been explained. Section 5 describes the Weighted Mix Estimation (WME) methodology for SOC estimation. The comparison of different SOC estimation methodology with the proposed SOC estimation methodology and load scheduling based runtime extension strategy is presented in section 6 under result and discussion followed by the conclusion in section 7 and acknowledgement in section 8.

II. Experimental Set up

The block diagram of experimental set up for implementation of WME method is given in Fig. 1. It consists of 12 volts 1.1 Ah VRLA lead acid battery used to power electric vehicle, ± 5 amperes hall effect current sensor for measuring current of battery and a voltage buffer circuit. The current sensor output and the battery terminal voltage were fed to the ADC terminals for data acquisition. The battery charging set up consists of an Agilent E3633A programmable DC power supply with constant voltage and constant current modes and a 60 MHz Tektronix TDS 1002B two channel digital storage oscilloscope.

High-speed 12-bit ADC AD7891 in parallel mode has been used for analog to digital conversion, which is interfaced with the Xilinx Spartan 3A FPGA, where the controller and data acquisition system is implemented. The RS 232 interface using MB32231 logic converter IC transfers the data to the computer for comparing data obtained with the reference data. A TDS 1002B two channel digital storage oscilloscope is used signal analysis and design testing. A Matlab based desktop simulation unit is used for plotting of the battery data. A 100 rpm, 42.51 kg-cm geared DC motor and a 12V and 35 watt headlight bulb were connected as load to the system.

III. Enhanced coulomb counter

The proposed methodology aims to improve the accuracy of the coulomb counting method by integrating an adaptive battery model, thus making the estimator a closed loop estimator. The coulomb counting method takes only current as the input from the battery and calculates the SOC based on the following equation(1).

$$SOC(t) = SOC(0) - (\int_{0}^{t} \eta I(t).dt / SOC(0)) \qquad (1)$$

Where SOC(0) is the initial SOC of the battery, SOC(t) is SOC at time instant, η is the coulombic efficiency .One of the major limitations of the coulomb counting technique is that it does not have an estimate of the initial SOC of the battery. This problem has been averted here by using the adaptive battery model, coupled with OCV-SOC mapping which provides better estimate of initial SOC of the battery [18]. The coulombic efficiency is the ratio of the energy that can be delivered across a load to the amount of energy delivered to battery while charging. The range of the coulombic efficiency comes in the range [0-1].The coulombic efficiency of the VRLA lead acid battery is found out in the offline mode to be .91 by discharging the battery in different load conditions.
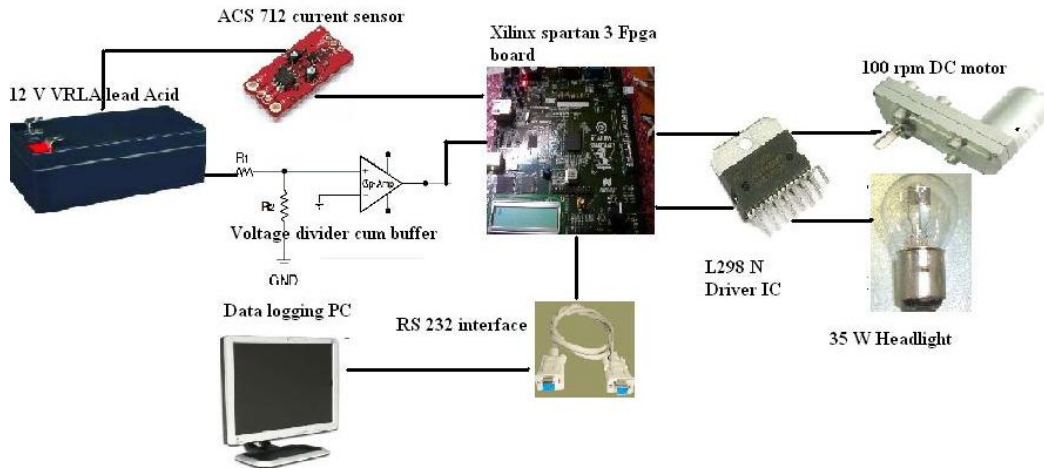
Figure 1.Block Diagram of Experimental Setup

As measurement errors and the external noises piles up with time, an inaccurate SOC estimation using coulomb counting technique is obtained. Thus it is essential to accurately sense discharge current of battery. For accurate sensing, discharge current was sampled at 244.14Hz. Output signal of Hall Effect current sensor is corrupted by external noise such as EMI interference and to denoise it an adaptive noise filter followed by a low pass filter was implemented. As shown in Fig.2, it was observed that the erroneous output of the current sensor bears a definite relation with the input to the current sensor. The observed relationship was exploited for extracting a factor of 1.5 which adaptively refrains the EMI to propagate to the output. This method was validated for the full range (0 – 5 amperes) of operation of the current sensor. For pertaining the computational accuracy of the results, functional units for floating-point adder and multiplier was implemented in FPGA [21].
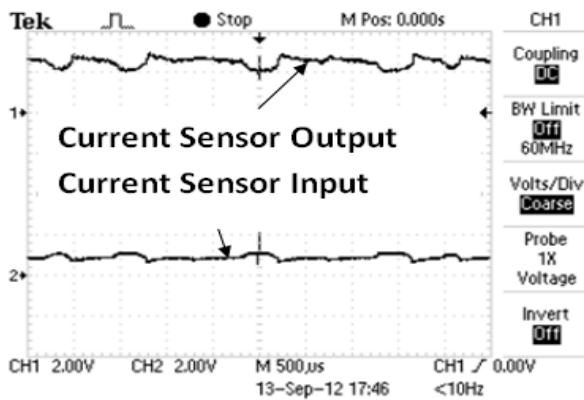

Figure 2. Current Sensor Input/Output

IV. Battery model

A model should describe the behavior of the system in the absence of the actual system. In literature a number of battery models are available such as analytical battery model, electrochemical model, kinetic model etc. All these models have their own advantages and disadvantages. The electrochemical model requires numerous battery parameters to be known, the electric circuit model is based on look up tables which increase the data complexity, the analytical

model though simple do not take into consideration the recovery effect.

Taking all these facts into consideration, an equivalent electric circuit model developed by the Saft battery company [7] was used to model the battery. The NRELS advanced vehicle simulator (ADVISOR) provides an RC circuit battery model in Matlab /Simulink platform which is used to study the vehicle performance as well as the battery behavior as they pass through different drive cycles. The schematic of the resistance –capacitance model is shown in Fig.3.The model simulates the performance of the battery to constant current (charge or discharge) and dynamic power cycles.
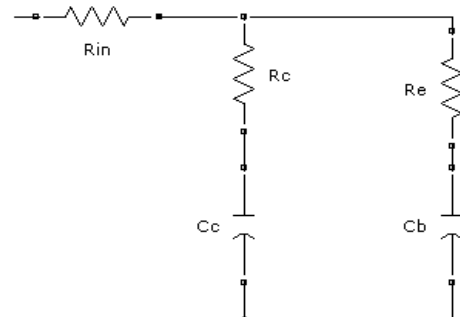

Figure 3. Battery Model.

The model consists of 2 capacitors and 3 resistors, where C_b is a large value capacitance used to model the bulk capacitance of the battery, C_c is a small value capacitance which models the surface charge of the battery, R_{in} represents the lumped resistance due to battery interconnections, R_e and R_c is the surface resistance and the end resistance which is used to model the dynamic response of the battery on connecting load.

The voltages across the bulk capacitance and surface capacitance are denoted as V_b and V_c. These parameters vary with aging, temperature and SOC of battery. In the present work, study of parameters variations with SOC is only considered. The battery parameters C_b and R_{in} are used to model the state of charge of the battery, as the variation in these parameters modulates the estimated terminal voltage and hence the OCV. The parameters C_c, R_c and R_e are used to

model the transient behavior of the battery discharged through dynamic load. Here V_0 is the output terminal voltage of the battery, Ib is the current flowing across Cb and Ic is the current flowing across Cc. The SOC of the battery was estimated from Vb and Vc obtained using equation (2) to equation (9) [22].

$$V_0 = IR_{in} + I_b R_e + V_b \qquad (2)$$

$$V_0 = IR_{in} + I_c R_c + V_c \qquad (3)$$

The algebraic manipulation yeilds,

$$I_b(R_e + R_c) = IR_c + Vc - Vb \qquad (4)$$

Now,

$$I_b = \frac{dVb}{dt} C_b \qquad (5)$$

Thus eqn(1.3) can be rearranged as

$$\frac{dVb}{dt} = -\frac{Vb}{C_b(R_e + R_c)} + \frac{Vs}{C_b(R_e + R_c)} + \frac{IR_c}{C_b(R_e + R_c)} \qquad (6)$$

Similarly

$$\frac{dVc}{dt} = -\frac{V_c}{C_c(R_e + R_c)} + \frac{V_b}{C_c(R_e + R_c)} + \frac{IR_c}{C_c(R_e + R_c)} \qquad (7)$$

Thus the net state space model of the battery combining the output terminal voltage V_0 is,

$$\begin{bmatrix} \dot{Vb} \\ \dot{Vc} \end{bmatrix} = \begin{bmatrix} \dfrac{-1}{Cb(Re+Rc)} & \dfrac{1}{Cb(Re+Rc)} \\ \dfrac{1}{Cc(Re+Rc)} & \dfrac{-1}{Cc(Re+Rc)} \end{bmatrix} \begin{bmatrix} Vb \\ Vc \end{bmatrix} + \begin{bmatrix} \dfrac{-Re}{Cb(Re+Rc)} \\ \dfrac{-Re}{Cc(Re+Rc)} \end{bmatrix} [I]$$

$$[Vo] = \begin{bmatrix} \dfrac{Rc}{(Re+Rc)} & \dfrac{Re}{(Re+Rc)} \end{bmatrix} \begin{bmatrix} Vb \\ Vc \end{bmatrix} + \begin{bmatrix} -Rin - \dfrac{ReRc}{(Re+Rc)} \end{bmatrix} [I]$$
$$(8)$$

The OCV of the battery is modeled by Vb and Vc together as shown in equation. Where $SOC_{Cb} = SOC(Vb)$ and $SOC_{Cc} = SOC(Vc)$ [5].

$$SOC = \frac{1}{21} \begin{bmatrix} 20SOC_{Cb} + SOC_{Cc} \end{bmatrix} \qquad (9)$$

Since the weightage of the voltage across the surface capacitance is less compared to that of the voltage across the bulk capacitance SOC can be considered to have one to one mapping with voltage across the bulk capacitance voltage and is approximated as the open circuit voltage.

A. Initial parameter calculation

The initial parameters of the battery was found out by using the OCV test and repeated discharge of the battery by hybrid pulsed profile discharge current [8] .The current pulses of 1 .1 A with duration of 5 seconds were used for discharge. The HPPC test was modified for battery electric vehicle by repeatedly discharging the battery after specific duration

instead of alternating between the charging and discharging profiles for the test. The initial battery parameters calculated for the 12 volts 1.1 Ah VRLA lead acid battery are listed in Table.1. Similar experiments were done also for Li-ion battery by which the battery parameters for the same were obtained.

*Table 1.*Initial battery parameters

Cb	Cc	Rc	Re	Rin
2112F	5.017F	.2 ohms	.2 ohms	.25 ohms

B. Adaptive tuning of battery parameters

The offline calculated battery parameters are fed to the model initially. The battery model takes only current from the battery as input and estimates the terminal voltage based on the initial battery parameters, but this is an open loop method as actual battery terminal voltage is not utilized. Hence the difference between estimated terminal voltage from battery model and the actual terminal voltage was used to adaptively tune the battery parameters in real time. The block schematic for adaptive tuning of battery parameters is given in Fig. 4.
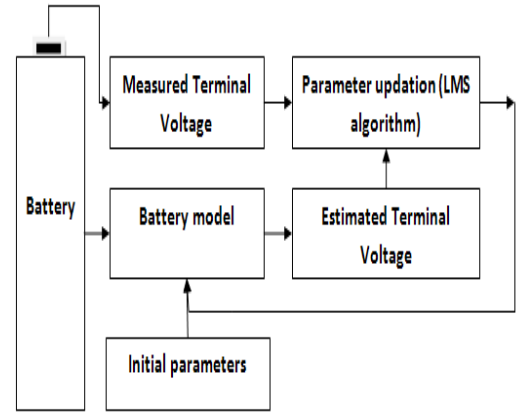

Figure 4. Adaptive battery parameter tuning

The states of the battery ie Vb and Vc are adjusted according to the square of difference between the actual battery terminal voltage and the model estimated value. The hypothesis selected for parameter tuning is the least means square algorithm. The LMS algorithm ensures the global minima avoiding the possibility of any local minima in the tuning process.

C. OCV to SOC mapping

Experimentation with the 12 volts 1.1 Ah VRLA lead acid battery provides the one to one relation of the OCV to the SOC of the battery during the discharge of battery as shown in Fig. 5. Similar results were obtained for the 7.4 V ,4.4 Ah Li-ion battery pack where the hysteresis effect has been discarded in the charging and discharging phase. The self discharge of the VRLA lead acid battery was also discarded as it is less than 1/20th of the nominal discharge current of the battery.

The battery was open circuited for 2 hours after discharging for every 10% of SOC before taking the readings of terminal voltage, thus allowing the terminal voltage to replenish back to the OCV. In practical electric vehicles open circuiting the

battery for 2 hours is not feasible. the battery model discussed above can estimate in real-time the OCV of the battery from the sampled terminal voltage. Thus obtained OCV is used to obtain SOC of the battery via the SOC –OCV mapping.The original mapping points were traced by 3 straight lines given by equation (10) with 99% confidence using curve fitting toolbox of Matlab thus reducing the order of mapped equation and computational complexity.
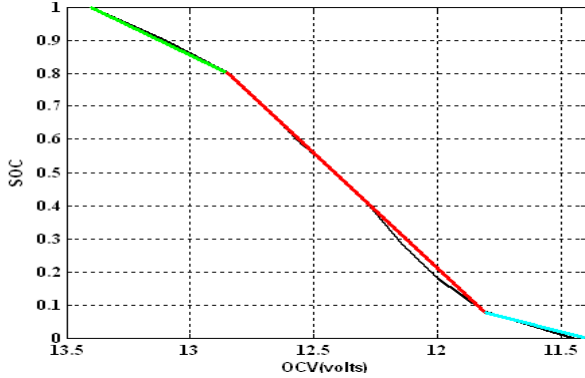

Figure 5. Relation between OCV and SOC

$$SOC = \begin{cases} .4272OCV - 4.596 & ,if \quad OCV >= 12.8V \\ .7938OCV - 9.306 & ,if \quad 11.8 < OCV < 12.8 \\ .2486OCV - 2.847 & ,if \quad OCV <= 11.8 \end{cases}$$
(10)

V. Proposed Battery State Estimator framework

A. Battery model based SOC recalibrator

The weighted mix estimation (WME) method utilizes a data fusion model expressed by equation (11) to inculcate the advantages of both the Enhanced coulomb counting estimation and the battery model based SOC estimation. Initially WME gives full trust to the battery model based SOC (SOC_v) i.e. $\alpha=1$, as it can adaptively learn the initial SOC from battery terminal voltage and discharge current.

After initial phase WME increases the trust on coulomb counting as it gives better SOC (SOC_i) estimate since the integral error accumulation is less. Again in the final phase of operation of battery the battery dynamics is efficiently replicated by the battery model based SOC (SOC_v), so the weights for SOC estimated by battery model is increased iteratively thus tracking the SOC of battery efficiently. Thus, by giving adaptive weights to SOC_i and SOC_v a better estimate of the battery SOC can be obtained throughout the battery operation stages.

The weighting factor (α) is defined as a function of state variables of battery model. The entire battery operational region was divided into sub regions, defined by state variables, with each sub region having a definite value of α found out by trial and error method.

$$SOC_{net} = \alpha SOC_v + (1-\alpha)SOC_i \qquad (11)$$

It should also be noted that model is a simplified linear model of the actual non linear dynamic battery system under specific operation conditions. The model uncertainties along with the shift in actual operating conditions may cause a change in the state variables which should not occur in actual linear time invariant system.

B. Fpga hardware implementation details

The SOC estimator is implemented in Xilinx Spartan 3A FPGA with device configuration XC3S 400 and PQ208 package and speed grade -4. The implementation details are shown in table 3 with a total utilization of 76 % of the total resources. An input clock of 4MHz was utilized but the implementation had a timing constrain of max frequency of 14.55MHz. The central part of WME is the 32 states finite state machine which has the enhanced coulomb counter battery model and the mix estimator implemented [21]. The estimated SOC is send to computer by an RS 232 serial communication interface.

A 32 bit floating point adder and multiplier is implemented which maintains accurate results. The parallel implementation of the adder and multiplier reduces the time overhead in execution thus making the real-time systems fast.

The state diagram of the machine is given by Fig.6. The block schematic of the FPGA battery state of charge estimator is given in Fig.7.
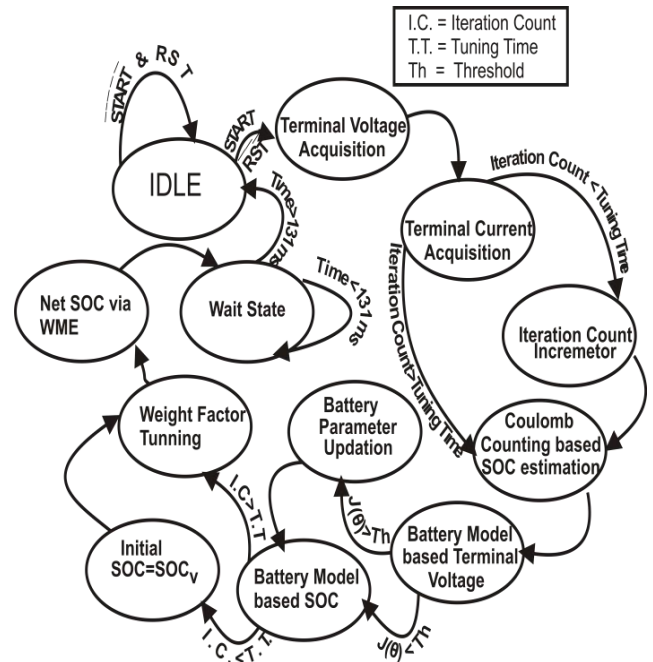

Figure 6. State diagram

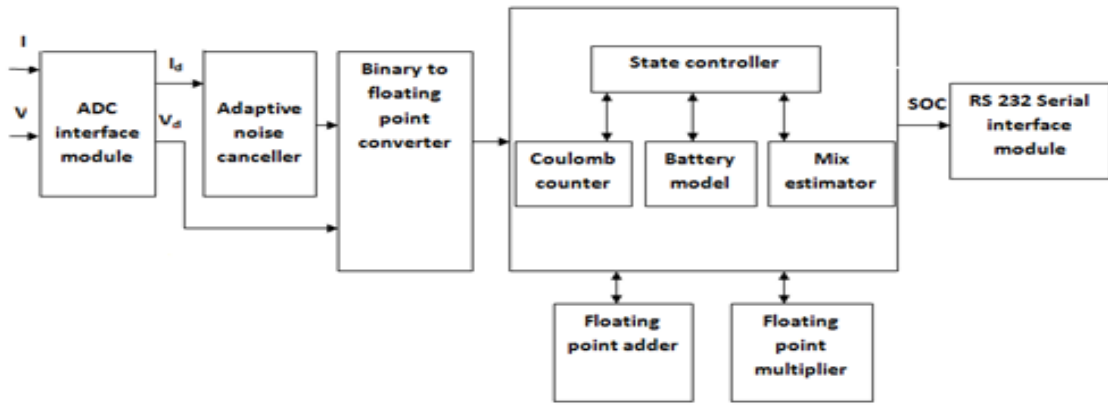The timing diagram of the full implementation is shown in Fig. 8.

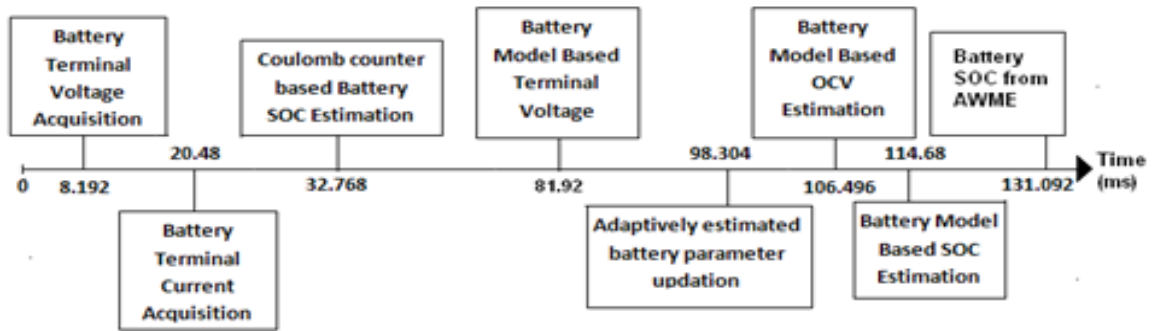**Figure 7.** WME estimator FPGA block schematic

Figure 8. Main Controller timing diagram

The state machine shown in Fig. 6 has 12 states with the initial state having iteration count reset to 0. When the external RESET is low and START is high the state machine goes to battery terminal voltage acquisition state and subsequently to the terminal current acquisition state. The iteration counter increments the count value on each iteration and goes further to the coulomb counter based SOC estimation state and estimates the terminal voltage from battery model subsequently. The battery parameters are updated in the parameter updation state based on $J(\theta)$, which is the mean of the square of difference between measured and estimated terminal voltage and further estimates SOC from battery model in the next state. If the iteration count is less than tuning time the initial SOC is assigned by the battery model based value. The state machine further goes to weight factor tuning state and subsequently to the WME state where the net SOC is estimated. The machine waits in the wait state until 131 msec to meet the timing constraints.

Table.2 FPGA Implementation details

FPGA resources	Total count	Utilized
GCLKs	8	5
LUTS	3584	2797
4INPUT SLICES	7168	5407
IOBS	141	25

VI. Results and Discussions

The result section is subdivided into two parts namely the state of charge estimation and predictive load scheduling.

A. State of charge estimation

For validation the experimental SOC of the battery has been calculated via offline calculation. Experimental SOC calculation needs the battery to be discharged to a set point against similar load conditions as of the execution of algorithms and measuring the OCV after resting the battery for 2 hours and finally utilizing OCV-SOC mapping discussed in section 5 to calculate the SOC of battery at the set point. For all results set points were distributed uniformly over the full discharge profile of battery as shown in Figs 9, 10.b, 11.b and 12.b. WME has been compared for accuracy and performance with enhanced coulomb counting, adaptive battery model and experimental SOC data from battery for four different experimental conditions viz. constant load, dynamic load profile 1, dynamic load profile 2 and a fictitious drive cycle for electric vehicle as shown in Figs.9, 10.a, 11.a, 12.a respectively.

In Fig.9 variations in estimated SOC by battery model (SOC_v) is due to the online adjustment of battery model parameters based on the feedback from measured battery terminal voltage as described in section 4.2. It is also observable that none of the implemented methods for estimation of SOC was able to track exactly the experimental SOC during the total discharge profile of battery. Compared to the experimental SOC data, both WME and enhanced

coulomb counting methods gave more nearby estimate of SOC from 100% SOC to 20% SOC region as compared to SOC estimate from battery model. But SOC estimated by enhanced coulomb counting was more erroneous after 20% SOC as compared to SOC estimates given by WME and battery model.
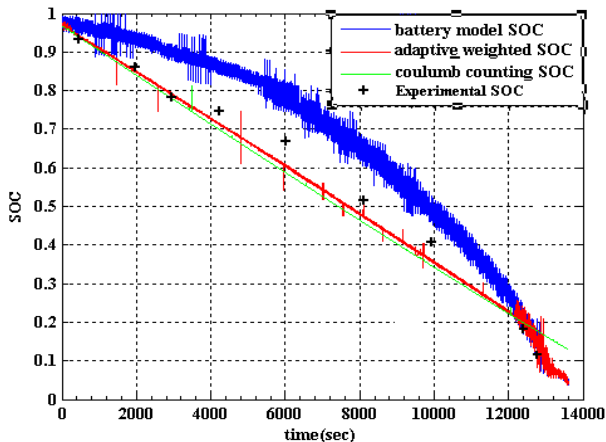

Figure 9. Constant load SOC profile

In dynamic load profile 1 shown in Fig. 10 a, battery was given discharge pulse of 0.82 amperes. This load profile was used to compare the accuracy of SOC estimation by WME and other methods when recovery effect of battery comes into action. Fig. 10b shows the plots for SOC estimation.
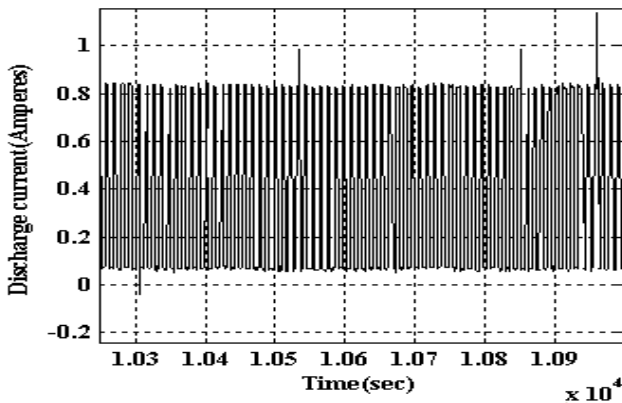

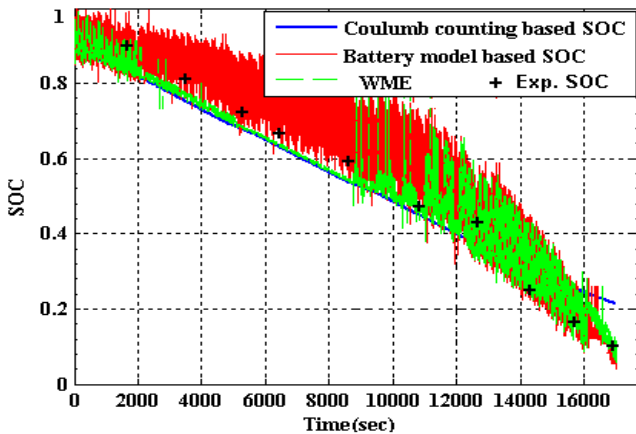**Figure 10 (a).** Dynamic load profile 1

Figure 10(b). Dynamic load profile-1 SOC profile

In dynamic load profile 2 shown in Fig. 11a, battery was given discharge pulse of 0.82, 1.5 and 2 amperes. This test is designed to excite cell dynamics as much as possible, and to investigate how the algorithm performs under complex and long lasting cycles. The result shows that the SOC fluctuates abruptly because of the varying loads for battery model and WME whereas that of coulomb counting is approximately linear and its value drifts away at the end of long drive cycle. Fig.11b shows the plots for SOC estimation.Fig.12a shows a fictitious drive cycle of electric vehicle and Fig. 12b shows plots for SOC estimated by WME and other methods. The changing amplitude of fluctuations in the SOC profile in the different stages of discharge shows that as the SOC of the battery changes the internal resistance also changes due to drift in chemical characteristics of the anode and cathode which comes in line with the findings of the work given in [23].The flat SOC-OCV mapping causes the abrupt fluctuations in the SOC in the adaptive battery model, which requires further filtering. As can be inferred from the figures, the amplitude of fluctuation is less that of WME compared to adaptive battery model alone.
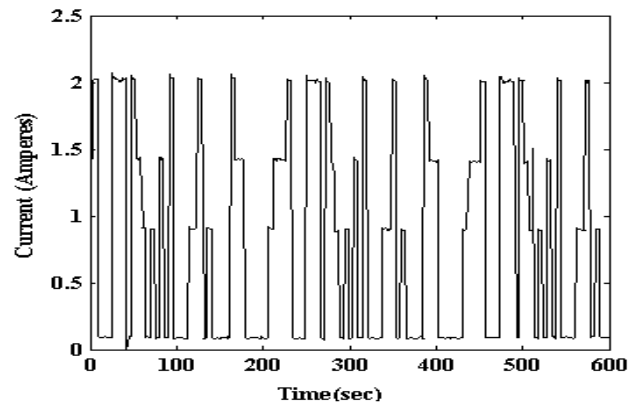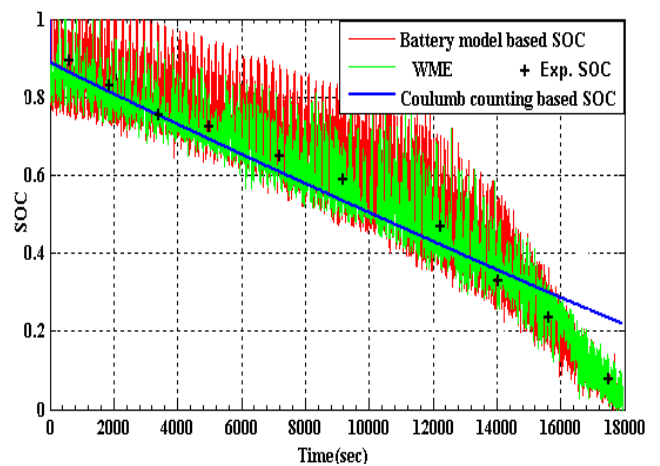

Figure 11(a). Dynamic load profile 2

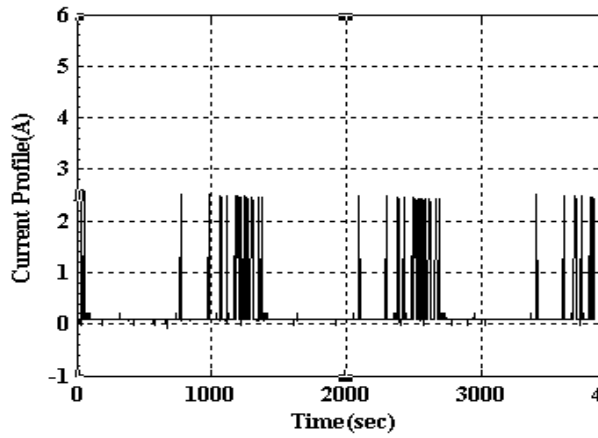**Figure 11(b).**Dynamic profile-2 SOC profile

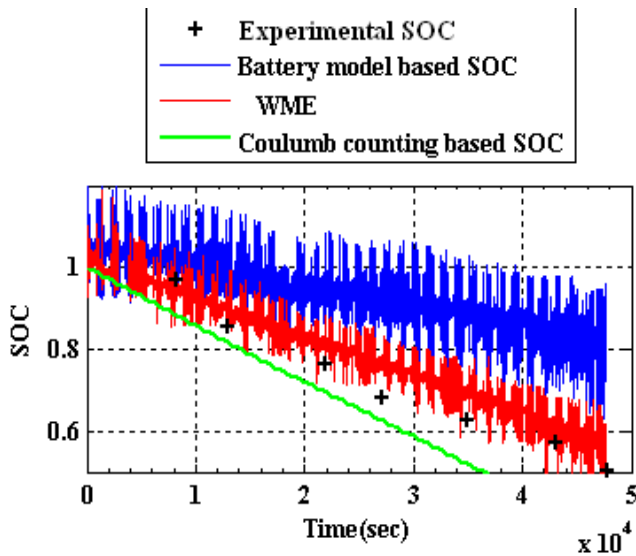**Figure 12(a).** Fictious drive cycle current profile

Figure 12(b). Fictious drive cycle SOC profile

Fig.13 shows the plot for root mean square error (RMSE) of methods for different experimental conditions. It can be observed from this figure that AWME has least RMSE in all cases except for constant load condition where enhanced coulomb counting has the least error. Enhanced coulomb counting method has RMSE varying from 0.02 to 0.06 while for WME variation was only from .0185 to .03594 under different experiment conditions. Thus it is evident that WME method gives the closest estimate of SOC to experimental SOC data for the battery at all levels of SOC and for all discharge profiles.
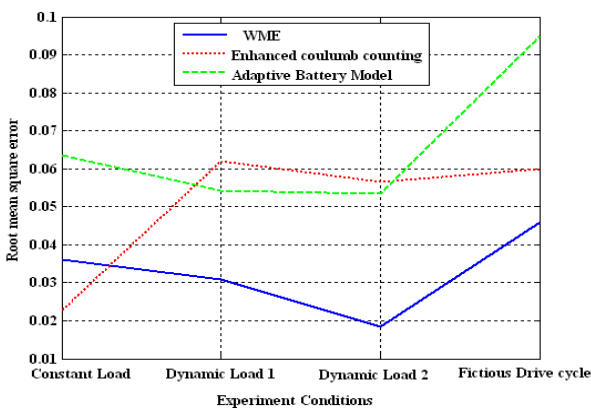

Figure 13. RMSE for all test conditions

B. Predictive load scheduling

The predictive load scheduling experimentation was implemented using a 100 rpm, 42.51 kg-cm geared DC motor and a 12V, 35 watt headlight bulb. A 7.4 V Li-ion battery was used for the above said experiment. The FPGA based controller controls the power delivered to the loads through an L298N Driver IC.

The speed of the DC motor and the load current in the other loads (headlight) of the electric car can be varied by varying the pulse width of the supply to these loads. Thus varying the pulse width applied to various loads is used to control the total load power delivered from the battery. Certain preset SOC points are set by the controller below which the controller reduces the total power drawn from the battery. The SOC estimated from SOC is used to predict the approximate SOC after 10 seconds based on the past load behavior. When the predicted battery SOC decreases, and reaches the preset SOC points the pulse width of the non critical loads viz. headlights, horn etc are reduced so that the speed of the DC motor is maintained and the car runs for a longer period of the time. Here the predicted SOC based control is implemented, which retains critical battery energy from dissipating to non-critical loads.

The pulse width control is done in the PWM controller block, which consists of 2 sub modules given in Fig.14, namely the Master controller and the Slave controller. The Master controller takes encoder input, Predicted SOC and Preset SOC points as inputs and sets a normalized value to the output register. The Slave controller generates a pulse whose net amplitude equals the normalized value set by the Master Controller. Each load has a separate register for control by which the net power to the load in the car can be controlled. The proportional integral controller implemented to maintain the constant speed of the DC motor given by equation (12).
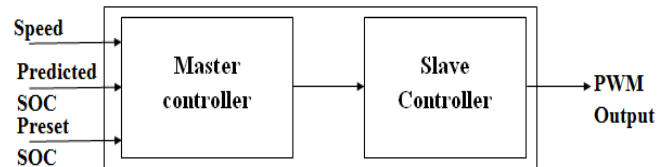

Figure 14. PWM Controller Block Schematic.

$$V = K_p * e(n) + K_i * \big(e(n) + e(n-1) + e(n-2) \big) \quad (12)$$

Where V=velocity, e(n)=difference between desired speed and the current speed (n-k)= difference between desired speed and the speed at $(n-k)^{th}$ time instant. The tuned value of the proportional constant and integral constants are $K_p = 2$ and $K_i = 4$.

The SOC prediction based control action duration of 147.656 msec. was obtained. The predictive controller action was taken 9.852 seconds before the actual occurrence of the event. The battery terminal voltage corresponding to the controller action is shown in Fig.15. The figure clearly shows that the terminal voltage of the battery increases slightly at the controller action points. This increases the run time of the battery for critical loads. The battery utilizes recovery effect at the control action points as the current drawn from the battery is reduced, thus increasing the runtime of the battery. The PI controller implemented maintains the constant speed of the DC motor throughout the battery operation time.
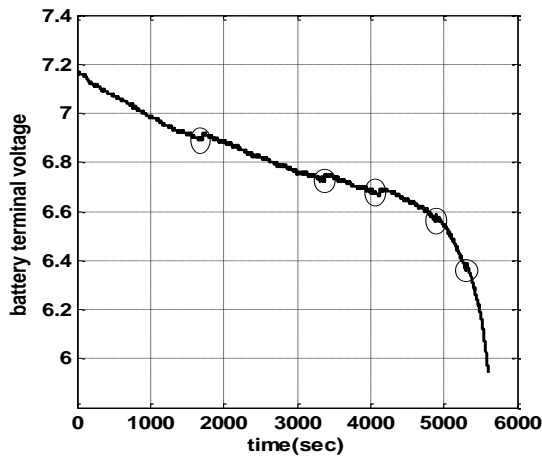
Figure 15. Terminal Voltage profile during Controller Action.

VII. Conclusion

This work proposes a strategy for an intelligent dynamic power management which can be utilized in Electric Vehicles. The following has been inferred from the above results

1) As shown in Fig. 13 WME gives best results for SOC estimation in comparison with enhanced coulomb counting and adaptive battery model, especially under dynamic load profiles which is the real time scenario for any battery operated device including EV's, where peak discharge current can momentarily rise above the rated capacity of battery (dynamic load profile 2).

2) WME would be ideal for battery powered electric vehicles where the load fluctuations occur in the range of ±5C, but in the case of hybrid electric vehicles it will be erroneous as the load fluctuations will be of the order of ±20C due to the frequent charging and discharging of the battery [24] .

3) The computational complexity of the above method is much lower than present state of art of SOC estimation methodologies.

4) The root mean square error for WME is found to be lower than 0.05 under all test condition as shown in figure 13.

5) The estimation based predictive load control as shown in Figure 15 has been also implemented in FPGA; The parallel execution in FPGA makes it an excellent platform for the implementation of predictive controller in real time, since both sensing and processing of the data can occur simultaneously. The figure clearly shows that the terminal voltage of the battery increases slightly at the controller action points. This increases the run time of the battery for critical loads.

Future aim of the work is implement the predictive load controller in actual electric vehicles.

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