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BATTERY CHARGE AND SOURCE ESTIMATION AS A PRODUCT COMPONENT

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Abstract:
This paper's goal is to present a low cost, non-conventional solution for battery state of charge estimation and external electrical input presence/absence for a commercial mobile, handheld device whose battery state of charge control is critical. This solution is based on treating and filtering a time series in real-time software, using the battery pack characteristic discharge curve and time series statistical features. The time series is composed of data that is sampled embedded in hardware, communicating directly with the machine's BIOS. The system processes this data and outputs a value that indirectly relates to state of charge, needing further processing to insure accuracy. The data stream is treated in a process that directly relates the output time series with state of charge through a transfer function, effectively treating intermediary conversions as black boxes to simplify analysis and implementation. This process can also detect if an external source is connected/disconnected by exploiting pre-detected features in the time series. This approach advantages are its low cost and simplicity, reducing hardware complexity and expenses; small dimensional footprint; mostly software-based; and centralization into the main hardware as low computational cost daemons, simplifying data consumption.

Keywords: Battery Modelling, Lithion-Ion Battery, Discharge Analysis, Instrumentation, Time-Series Analysis, System Compensation, Optimization, Product Design, Low Cost.

1. INTRODUCTION

Battery powered systems are present in everyday life, from toys to vehicles, suffering from a large diversity of consumption and stress conditions. Battery state of charge estimation is fundamental to assure best use of resources, avoiding overuse and worst-case scenarios in critical applications. Battery technology and management systems are fundamental parts in designing good, reliable products, which can be observed in recent industrial efforts to further advance battery performance, as well as managing energetic resources, as discussed in Barua et al. (2009). Managing battery resources is specially important for mobile embedded systems, because external power sources may not be available for long periods. VIACAST© stream encoder line of products can be classified as critical devices for live streaming, as they provide an essential communication service that generally has few to no redundancy. Because of the application's critical nature, it is essential to provide ways of measuring battery state of charge accurately for better, informed resource management.
There are many known technologies and methods to estimate battery usage, developed for general use or specialized solutions. Kocic et al. (2012) discusses a general implementation that can deal with multiple batteries, of distinct compositions. This approach is generic, but it is complex and requires many hardware components, making it impracticable for an encoder device. A mostly software based approach is presented, aiming at simplicity and hardware cost reduction, as production cost reduction is essential to enable competitive final prices for the final consumer. Differing from Aslan and Yasa (2019) decentralized processing, data-hungry approach, this paper's technique is based on pre-modelling the power system and treating data in the central hardware. The modelling approach is black-box based, but respectful of previous feature observations in literature. Its treatment is centralized to reduce external hardware, and requires an efficient implementation to be an insignificant processing burden addition.
A software focused approach can be more easily ported and adapted for similar systems and other embedded applications. This is very important, because it supports changes in systems components, liberating its use in different hardware, that operates in distinct logical levels and consumes power differently. It also simplifies the adoption and interchange of distinct battery packs and technologies. In the present paper, the studies were conducted on a Li-Ion battery pack, but the methodology can be used in other battery technologies.
The following section presents how battery state of charge models are produced, and their relevance. In section 3 it is presented the system components, the modeled elements

and instrumentation. In section 4 sampled data analysis is discussed to evaluate how to use output information. In sections 5 and 6 software methods for estimation and porting results are shown. Concluding, discussions about the system implementation and effectiveness are made.

2. BATTERY MODELS

A charge/discharge model is important to predict how the battery properties will behave as its capacity is depleted. Batteries' tension vary with their state of charge, the voltage dropping as its charge reduces. Among the various modelling techniques to generate a discharge function, the most suitable for this application are the impedance model and empirical methods (Shepherd, 1965) (Costa et al., 2017). This is justified by factoring that other models, such as the battery electrochemical model, are too complex and do not add much relevant information to build a simple empirical polynomial approximation.

The discharge model, using output voltage as state variable, is given in Figure 1, where there is internal impedance, a tension model and a current integrator.

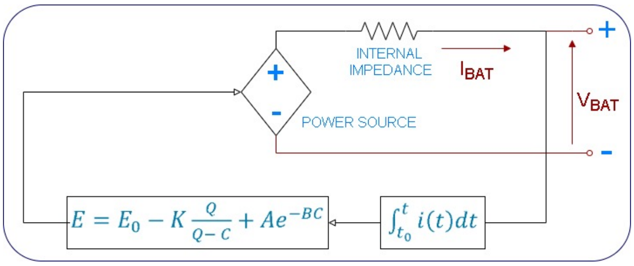


Figure 1. Discharge Block Model - Adapted from Costa et al. (2017)

Under the assumptions of constant internal properties (impedance, immunity to current, temperature and memory effects), no self-discharge, constant output current and reversibility (same behavior for charging), the common literature discharge model is introduced in Equation 1:

$$E(t) = E_0 - \frac{KQ}{Q-C} - Ri + Ae^{-BC} \tag{1}$$

Where $E(t)$ is the battery supply voltage, E_0 is internal voltage, K is the polarization constant, Q is the battery's nominal capacity, C is the consumed charge, R is internal resistance and i is time constant current. A, B and K are determined using empirical values. E and C are time dependant. This equation is non-linear, were each component dominates the discharge behavior in a distinct zone.

Li-Ion batteries, which were used in this design, have three very distinct discharge zones in their working voltage range (Fuller, 2014). In discharge order, there is an exponential zone, nomiinal (linear) zone and a terminal zone. This behavior can be observed in Figure 2, where the discharge curve exhibits very distinct behavior in each zone. In practice, the curve rests in exponential or terminal zones for a short amount of time, being mostly in its nominal zone. The specific battery pack and cells are discussed in the next section.

The previous non-linear model presented at Equation 1 is useful for comprehending how the battery behaves, but it is proposed that in practice internal parameters are completely abstracted, as the information in a white or gray box model may relate to a physical property, but its mathematical model is more complex and may not adhere as well as a black box model. The non-linear model is further explored in section 4. A model proposing that the state of charge - voltage relationship does not depends on the average drawn current (Zhang et al., 2018), may be suitable. Ignoring electrical, chemical, thermal and other physical characteristics to use only empirical data can be beneficial to simplify modeling. In the proposed methodology a polynomial curve is generated from empirical constant power output data, whose normalized inverse can be directly used to estimate the state of charge.

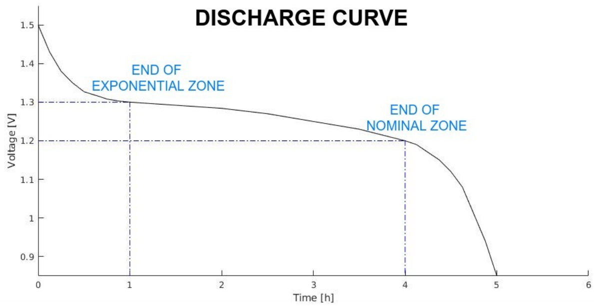


Figure 2. Li-Ion battery discharge curve behavior - Adapted from Fuller (2014)

3. SYSTEM AND INSTRUMENTATION

The abstract electrical system is simple, being composed of a power source (external source or battery), a varying impedance (encoder hardware) and an instrumentation device to measure voltage. In the following subsections each component is discussed.

3.1 Electrical Block Diagram

The electrical system can be simply modeled as a time varying source, as its output voltage decays with its battery state of charge, coupled with a time varying power consumer and an estimation device, as Figure 3 displays. The device may change its energy needs based on its processors load and other external influences. To properly study the system, power consumption is fixed constant to generate analysis data.

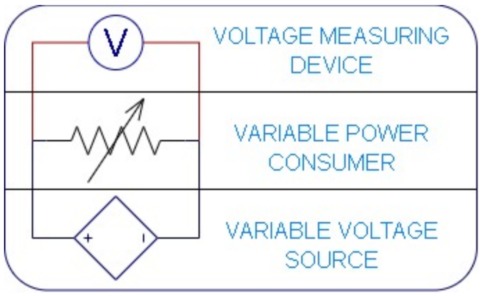


Figure 3. Simple Electrical model for instrumentation

To estimate the state of charge, the input voltage is measured using an instrumentation device inside the encoder, directly communicating with the main processor. The device is always sampling, as long as the encoder is being fed. It was designed to be embedded and to not require external signaling, in the form of an user explicitly requesting information, to work.

3.2 Battery type and arrangement

The specific used cell is Li-Ion composed, with nominal tension at 3.6 V and capacity at 4500 mAh. Its capacity tolerance range from 4400 to 4600 mAh. Its maximum safe internal voltage is 4.2 V and minimum 2.75 V. Voltages outside this range will accelerate fatigue and can permanently damage the cell.
The battery pack is composed of two parallel four series cells. Thus, its nominal voltage is 14.4 V and capacity 9000 mAh. Tension values may range from 16.8 to 11.0 V. Its original capacity may range from 8800 to 9200 mAh. Charge safety parameters, handling instructions and protection circuits are outside the scope of this paper.

3.3 Instrumentation

The instrumentation device was built using a voltage-to-frequency converter, the IC LM331 from Texas Instrument. This component provides a specific range of frequency based on the arrangement of peripheral components, resistors and capacitors. Figure 4 shows how the IC can be used as a voltage-frequency converter.

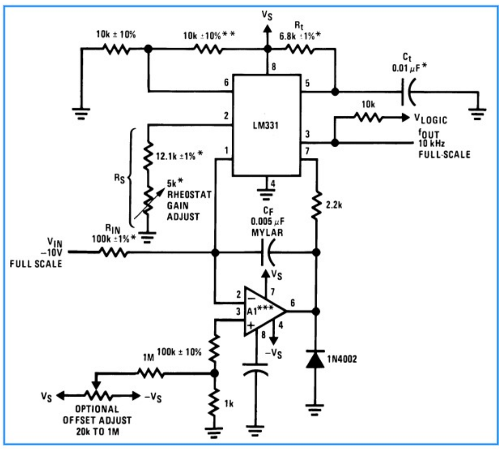


Figure 4. LM331 connections and periphery

Following the arrangement in Figure 4, the output frequency is given by Equation 2. In Equation 2, f_{out} is the output frequency, V_{in} is the measurement input frequency, R_s, R_l, R_t and C_t are peripheral resistances and capacitance.

$$f_{out} = \frac{V_{in}}{2.09} \cdot \frac{R_s}{R_l} \cdot \frac{1}{R_t C_t} \qquad (2)$$

The component is powered with 5 V , reading high-voltages up to 40 V (which fits on the batteries voltage requirements), and provides a wide range of full scale frequency, from 1 Hz to 100 kHz. V_{in} is captured prior to the main board filter.

The voltage captured by the device is converted to frequency and appropriately fed into the machine BIOS and then to the Operational System, as shown in Figure 5, where the output data can be accessed by processes. BIOS and Operational system conversions are treated as black boxes in this paper. The BIOS and Operational System constitute a discrete converter (Fadali and Visioli, 2013), meaning that the entry frequency will be converted into a discrete value in small ranges, and has a sampling limitation. This issue is further discussed in Section 4.

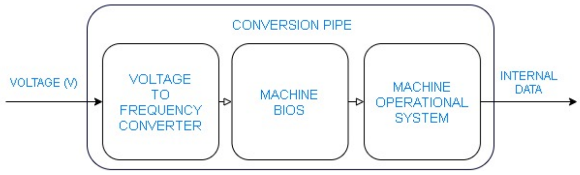
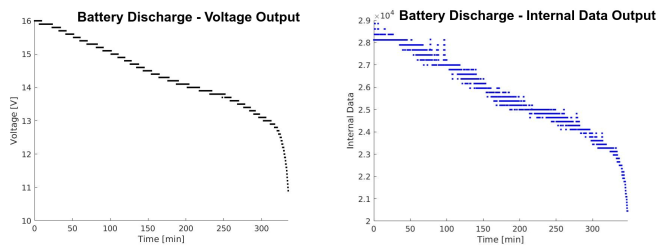


Figure 5. Voltage conversion into internal data

4. DATA ANALYSIS

First it is fundamental to study the relationship between the internal data and voltage. This can be accomplished by using an external device to directly output voltage. Both being sampled simultaneously can be compared to check linearity, in multiple discharge experiments. It is useful to inspect if the internal data time series will have similar behavior to that of the battery voltage.
Sampling frequency is fixed at 2 Hz, sampling until the voltage drops beneath 11.0 V. This sampling frequency was chosen due to an output limitation in the conversion pipe (Figure 5), and to match the operational sampling frequency. The experiments were conducted five times to use an average value to produce further results, using all five experiments. In order to improve accuracy, a five element moving average window was applied to internal data, as its discrete values are too distant. The results can be observed in Figure 6 with brute data and fitting, where Figure 6a is output voltage in time, Figure 6b is output internal data in time and Figure 7 is the linear correlation between voltage and internal data comparing time series. Voltage resolution is 0.1 V. The experimental data comports very similar to theoretical models.



(a) Voltage as output (b) Internal data as output

Figure 6. Experiment to inspect for correlation and generate a polynomial transfer function

Using Equation 1, the data in Figure 6a, data gathered from instrumentation, and the methodology described in Costa et al. (2017), the impedance model parameters can be calculated. V_{full} is set to 16.1 V, V_{exp} to 15.7 V, and V_{nom} to 14.4 V. Q_{full} is set to 9.10 Ah, Q_{exp} to 8.75 Ah,

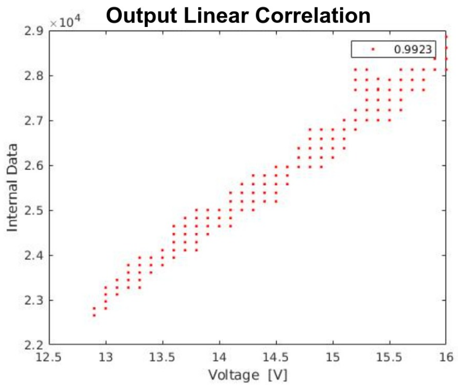


Figure 7. Linear correlation between output voltage and internal data, with a value of 0.9923

and Q_{nom} to 4.30 Ah. Current i was measured to be approximately 1.159 A, treated as a constant. Resistence R is negligible, so it was approximated to 0.0. Other parameters are calculated based on the previously presented values.
The resulting formulation is displayed in Equation 3. The standard deviation of this model from the obtained data is 0.3709 V. An overplot with validation data, captured using the same methodology and parameters, can be observed in Figure 8. Qualitately it can be observed that the model did not have good addhesion due to the non expected behavior in the data, in its relative slow drop from minutes 200 to 250 and its very sudden drop at minute 330. This model is considered not suitable for the following processes.

$$E(t) = 17.254 - \frac{14.1358}{9.1 - 1.159t} + 0.4e^{-0.3975t} \tag{3}$$

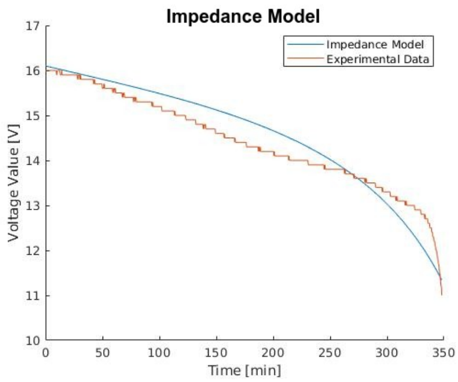
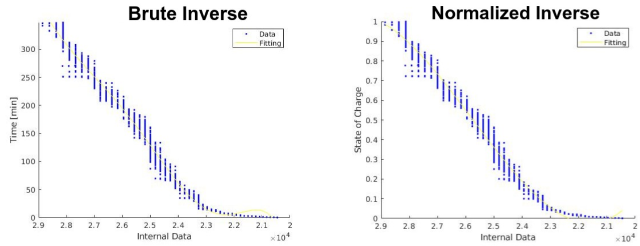


Figure 8. Generated Impedance Model and Validation Data

To produce a transfer function (Hayes, 1998) in the form of a polynomial function from internal data to state of charge it is first necessary to perform several discharge experiments, generating an average discharge function, as was shown in Figure 6b. Voltage is treated as static regarding the state of charge. This function may then be inverted to generate a $Time$ x $Voltage$ inverse relation. It is essential to normalize in time the generated inverse relation, which is the state of charge (Zhang and Lee, 2011), ranging from zero to one, that can easily be converted in percentage by multiplying by one hundred. The necessary supposition is constant power consumption, that was guaranteed during the experiments.

The resulting brute relation and normalized relation can be observed in Figure 9, where a simple linear function would be suitable to represent most of the curve, except the exponential and terminal zones. Figure 9a could be directly used to estimate the remaining operational time, but in daily practice, power consumption is not constant, so displaying state of charge is more useful and accurate. Inverse Normalization is done by dividing the current sample time by the maximum time, resulting in Figure 9b.



(a) Brute Relation (b) Normalized Relation

Figure 9. Empirical inverse relations

4.1 POLYNOMIAL REFERENCE EQUATION

To generate the polynomial transfer function it is necessary to choose a polynomial order. Different methods to generate a polynomial function were considered, such as the NARMAX method (Correa and Aguirre, 2004), but due to the increased computational cost of a polynomial with a larger amount of terms, a simpler model generation choice was taken. The choice is done based on simplicity, as it must be calculated periodically in a real-time process, and quality of adhesion, minimizing the error between the fitted curve and sampled data. Lower order polynomials are preferred, choosing higher order polynomials is justifiable only if the adherence gain is high.
After comparing results from lower order polynomials, the choice is a third order polynomial, because higher orders did not demonstrate justifiable gains. Equation 4 is generated:

$$SoC = 100(aI^3 + bI^2 + cI + d) \tag{4}$$

Where a, b, c and d are constant coefficients, I is internal data and SoC is the state of charge in percentage. The least-squares minimization method was applied, obtaining coefficients a, b, c and d valued respectively as -0.00364776, 0.28200477, -7.07657266 and 58.01836147. Because the transfer function is treated as static (Verly et al., 2011), the standard deviation may be used as metric. The obtained value is 4.214%. Optimization based on large datasets, using Gradient Descent, is an option to reduce overfitting on a single device, better representing the product, to be explored on a future work.
This generated function can be used as a reference for other systems, sparing the time to fully reproduce the previous discharge experiments, requiring only compensation over Equation 4 to be applied in a similar system. This is further discussed in the next section.

4.2 VALIDATION AND DISCUSSIONS

In order to validate the generated polynomial transfer function it is essential to run a validation procedure. This procedure is to perform another set of discharge experiments, but in this sequence comparing the estimated state of charge with the real state of charge in time format, observing error (deviation). The filter and algorithm parameters values are, sampling rate of 2 Hz, internal data boundary $[22.4, 30]$, and average mean of 100 samples. The process takes approximately 50 s to start outputting values. These parameter values were obtained after analyzing the time series results with arbitrary parameter choosing. The resulting sampled comparison can be observed in Figure 10, with sampled data, linear fitting and the ideal perfect fit line.

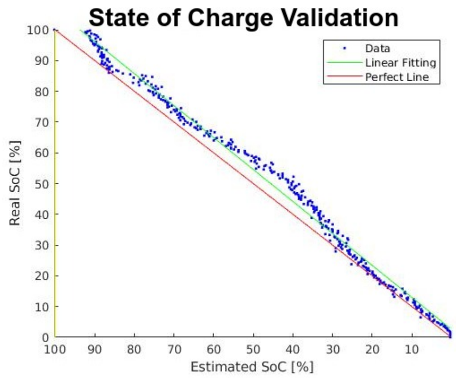


Figure 10. State of charge estimation validation

The obtained standard deviation value is 3.890%, being actually smaller than the data set used to generate the polynomial model. The observed results are satisfactory for professional practice in this application as long as the system internal parameters are time constant or have suffered little variation. The common modelling methods use constant parameters (Fuller, 2014), but in practice time has an effect in battery behavior. As portraited in Safari et al. (2010) battery capacity and other parameters degrade with time and use, which could affect the estimation ability. For the specified cells maximum capacity is reduced by 90% after five hundred cycles and by 80% after a thousand cycles. This could affect accuracy after a few years of use, requiring corrections on the transfer function.
In the next section methods for further improving estimation and robustness are discussed, as well as how to port model results into other machines and systems.

5. STANDARDIZATION AND OPTIMIZATION

In this section methods for porting model results into similar systems are discussed. To reuse results it is necessary to standardize a filter pipe. The proposed pipe uses the original estimation algorithm, employing the same obtained polynomial equation into all systems, using modifiers to improve accuracy for each particular machine/battery pair.
These modifiers are pre and post filters, that will change the time series with the purpose of improving estimation by adjusting data following their transfer function, as Figure 11 suggests. The compensation values can be saved into a preset file, to be used by the estimation process. A quick and dirty implementation to rapidly obtain corrective factors, is to fix pre compensation at the neutral

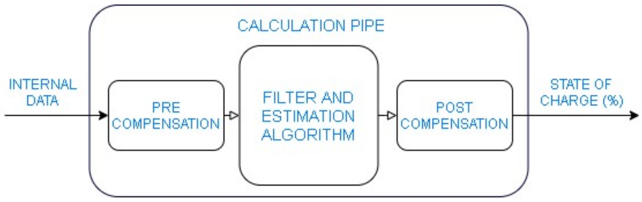


Figure 11. Internal Data conversion into state of charge

value (1), as its final output effect is non-linear otherwise, and feed the present time voltage into a comparison program, that contrasts with estimated voltage from internal data to generate the post compensator. The proportion (input voltage divided by estimated data) can be used as modifier. This can be used to quickly generate a corrective factor that does not require a full discharge sampling. This method is not robust.
To ensure accurate results it is necessary to regenerate the polynomial transfer function or to calculate optimized compensators. The second approach is further explored, as it requires less sampling experiments.

5.1 Optimizing Compensation

In order to improve results it is necessary to establish an optimization problem and a method. Zhang and Lee (2011) discusses many different mathematical approaches to improve estimation of battery parameters. In this paper the corrective factors are simple constant pre and post compensators to the main algorithm (Figure 11), acting as magnitude filters. The optimization problem is defined in Equation 5, as the minimization of a cost function using least squares to compare experimental estimation and ideal data, a quadratic optimization problem (Patriksson et al., 2016).

$$min(\sum(x_s^i - C \cdot x_s^r)^2) = min(F(x^r)) \qquad (5)$$

In which x_s^i and x_s^r, are respectively the ideal and estimated state of charge values for sample s. C is the compensator to be optimized. $F(x^r)$ denotes the objective function for array x^r. This method aims at optimizing each filter separately, first the pre compensator then the post compensator.
Three different methods to search for the global minimum were considered. In the first method, the values are obtained using a deterministic approach, using the derivative to guide towards a solution. The second method uses a metaheuristic approach, to avoid local minima. The third approach uses brute force.
The first alternative is to choose a fitting algorithm for a quadratic programming problem (Lin et al., 2012). It must be noted that the state space might be nonconvex. An approach is to use a simple hill climbing method, using the derivative towards a local optima.
The second alternative for this problem to systematically obtain diverse solutions, is by using a metaheuristic approach, as the Simulated Annealing (Weyland, 2008), which is a method for accelerating the process towards diverse solutions. To set the algorithm parameters, it is fundamental to observe qualitatively the specific optimization problem. As the local minima are likely to be clustered within a region of the state space, due to data distribution, faster cooling might provide better results.

The third approach is to simply use a brute force search within the expected solution cluster, by setting a start and end point and a constant step.
All arbitrary parameters are set empirically.

5.2 Results

First, the estimation algorithm and polynomial equations are ported into another system without changes in any parameters. Then, a set of discharge experiments (3), concerned only with internal data to estimate state of charge are performed. Finally, an optimization round is applied to the pre and post filters, aiming at the improvement of estimation, by minimizing the objective function (Equation 5). Unfiltered estimation data can be observed in Figure 12, comparing the stream of estimates with the correct values (perfect line). The yellow line marks the maximum real capacity. The standard deviation is 25.698%.

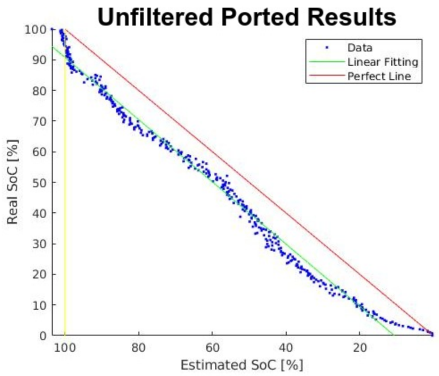


Figure 12. Unfiltered results obtained in a different system

Due to the small search space, the brute force method was quickly inferred to be the best option for this problem. By searching from 0.850 to 1.150 with 0.001 step, a best solution was quickly identified.
Optimization is first applied into the pre filter, obtaining a value of 0.973. Then, its result is taken and it is applied into the post filter optimization, obtaining a value of 0.996. The optimized results can be observed in Figure 13. The other optimization methods arrive at the same values.

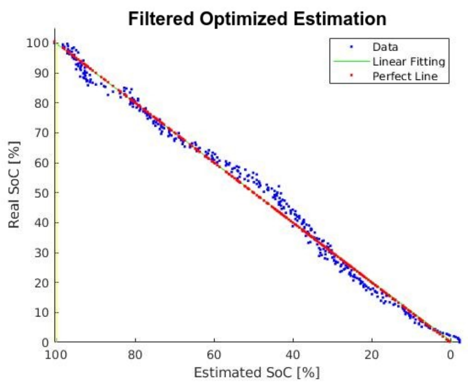


Figure 13. Optimized results obtained after porting to a different system

The final standard deviation is 1.326%, which is a significant improvement from unfiltered state of charge estimation. It is hard to compare the three techniques performance, as the convergence and iteration times are strongly related to parameter selection for the deterministic and probabilistic options, but using literature we can say that Simulated Annealing scales better into larger search spaces with more dimensions, and the hill climbing policy can generate faster results on smaller search spaces, and is better applied into convex search problems. Brute force is faster because for this particular problem the optima is centered at 1 with small deviation. Comparing development and implementation time, the brute force option is faster than the other two. Between the other two, the hill climbing method has less parameters to be set.
Co-optimization may generate faster results, as it can set pre and post compensators in a single processes, but requires a more complex coupled algorithm, which is not explored in this paper.

6. SOURCE DETECTION

Power source origin detection is important to display to an user, as it is a reminder to plug the encoder in an external power source as soon as possible. The displayed information can also be used to judge if the source is correctly connected and the device is being properly fed.
To determine if the machine source input is battery or external source, there are many methods, commonly hardware or firmware based. Huang and Abu Qahouq (2014) exploits battery alternate current impedance variation to estimate state of charge, which could be used to determine whether the power source was changed. This paper approach is not based on including more hardware, as it would increase assembly price and complexity. Instead, internal data time series are explored, observing patterns in its statistical properties as the battery charges/discharges, constituting a software-based technique, which is faster than directly observing if the state of charge is increasing or decreasing with time.
Unfiltered internal data sampling in a small time frame can be used to observe quirks in the time series, to develop an exploitation algorithm to estimate whether the power source is the battery or an external source. Figure 14 shows how the unfiltered internal data behaves on a small time frame, where charge/discharge effects can be neglected, for a battery tension value of 14.5 V. An external power source is plugged at approximately 4.5 minutes and removed at 6.2 minutes with its voltage level at 16.5 V, also charging the battery. Sampling rate is fixed at 2 Hz. The external power source voltage level is relevant for this algorithm and is discussed in the results subsection.

From Figure 14, it can be observed that internal data tends to alternate between two values for a given voltage, transitioning into a lower step as its charge depletes, as can be observed to start at the 2.8 minute mark. Or into a higher step as the external source is plugged, at 4.5 minutes. This quirk can be coupled with a window filter using a statistical property to detect external source plug/unplug, as it is present at any state of charge.

6.1 Extreme Comparing Window Filter

Window filters (Lesti and Spiegel, 2017) are a family of filtering methods normally applied in real time discrete

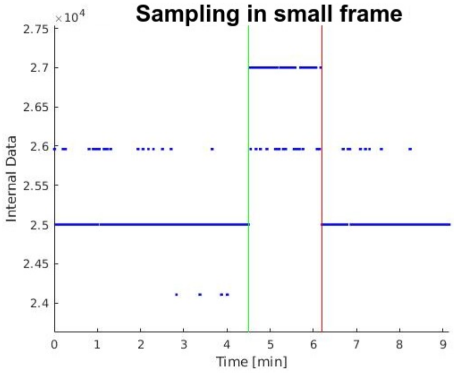


Figure 14. Internal data sampling in a small time frame

processing to treat a time series. They work by using the n last samples to correct the latest sample under some mathematical law. The most common and popular window filter is the moving average filter, that takes the average of the last n samples and substitutes the current value in the output stream. This effectively works as a low-pass filter, adding inertia to quickly changing behavior. Differing from Bin et al. (2006), the algorithm is not suitable for this application, as the filter needs to highlight an abrupt change in stream value.

The properties observed were mode, anti-mode, maximum and minimum window values. After empirically testing each filter, using a window of 5 samples, it was observed that the best results came from contrasting maximum and minimum values considering an infinite past horizon.

Using this contrast technique it is only necessary to store the past horizon maximum and minimum values and compare their difference, until it is higher than a specified difference δ, then the current value replaces both past horizon values. If the current window output sample maximum is higher than the past horizon maximum, it substitutes the value, the same applying for the minimum. If δ difference is achieved when the maximum value is substituted it means that the external power source was plugged. If it happens when minimum value is substituted it means that the external power source is disconnected. This technique is not immune to false transition flagging, but it possesses self corrective nature, as the internal data values will change based on whether the battery is charging/discharging.

6.2 Results

The parameter values are 5 for window size and 2.1 for difference δ, and the past horizon is infinite. They were obtained empirically. The first value is used to populate the window when the source detection process is started.

To test the algorithm, an online consumer process is used in the machine, then the external source is connected/disconnected in rapid successions to observe if the process identified the transition successfully. In the test carried in Figure 15, the battery voltage level is at 14.1 V. The red line level indicates if the external source is on (HIGH) or unplugged (LOW).

The observed results in Figure 15 used a small time frame, but all transitions were correctly flagged, in about one full window. A set of long time framed charge/discharge (3) tests to inspect for false flags was performed, resulting in one false accusation per test in average, caused by outliers. All occurrences were self corrected in under two minutes.

Source detection can run in parallel or in the same process as state of charge estimation. The δ parameter also needs to be corrected to be used in a ported system. A modifier defined by the ratio of the original internal data maximum by ported system internal data maximum is used to correct the δ value in each machine.

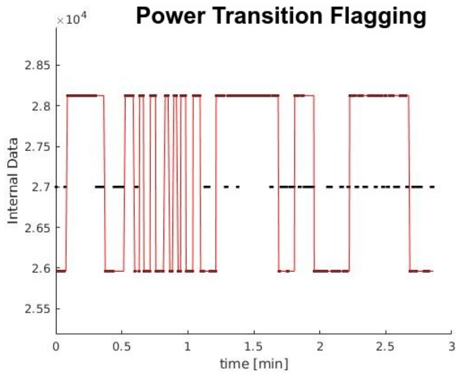


Figure 15. Quick power source transitions

The main problems observed in this approach arise from initial condition, which must come externally or be assumed, and when the battery is close to fully charged, as its voltage level difference from the standard external source is small. The fist problem is corrected as the battery charge is consumed/filled and the second would require additional criteria to be inbuilt in the source detection algorithm, which is not treated in this paper, as the battery state of charge is close to full this flag is not considered urgent.

7. CONCLUSIONS

The Li-Ion battery pack had a similar behavior to the predicted in literature. The understanding of the relationship between voltage and state of charge was useful to guide and review decisions on instrumentation and estimation, as the chosen instrument coupled with the BIOS and Operational System is efficient at outputting internal data that is linearly correlated to voltage. Based on the internal data behavior it was decided that a simple polynomial equation would suffice in representing the internal data-state of charge transfer function.

The specific instrumentation IC, LM331, was chosen because it is originally used to estimate revolution speed in fans and blowers. According to Rusu and Grama (2008), voltage and speed correlate linearly through the transfer function, meaning its final output can be backtracked to voltage easily. The LM331 IC is also low cost, readily purchasable, and requires few peripheral components. It is also simple to solder and embed in the product.

About the inverse equation, a low-order polynomial approximation is used because of its simplicity and because it allows for a faster, more efficient calculating consumer process. Its unfiltered validation results were satisfactory, although a high order polynomial, non-polynomial fitting or series-coupled filters could generate better results.

To port the algorithm with previous results into other systems it is fundamental to compensate for component differences. It was standardized the use of a common polynomial equation for speed and measure of variation in the systems.

These differences arise from hardware uncertainty, in the form of battery parameters and machine/instrumentation electrical impedance. The fastest simple way to compensate estimation under polynomial standardization was to apply modifiers.

The source detection algorithm is a simple contrasting moving window filter, which is implemented as a light load process. This approach favors software and requires no additional hardware to operate, being simple to adapt or to further develop.

There are many possible ways to improve results, a number of them requires more items or expensive hardware, while the others add complexity or computational cost into the software processes. Nonetheless, it is important to list them as they might be suitable in the future.

One way to improve source detection using firmware is to branch connect the external power source into a general purpose input pin on the main board, which may be directly accessed by the operational system. This approach is not used because not all processors have these pins. A way to improve estimation results is to use a more specialized, expensive hardware that directly measures and estimates voltage, communicating to the main board. This approach is not used because it adds hardware and production costs.

Further works include searching for other low cost and concordant hardware instrumentation solutions, as well as batteries and hardware with lesser variability. Concerning methodology, to use a larger database, to reduce overfitting and improve validation. Concerning the estimation software, embedding a self-regulating, learning solution may solve the problem of over time behavior change, as the batteries slowly degrade with fatigue, losing capacity and changing its state of charge-voltage relationship.

Finally, both state of charge estimation and source detection techniques were deemed satisfactory to be used in a commercial encoder by VIACAST©, aiming at the best cost-benefit to the consumer with good performance. Both were implemented as daemons in the C language, to be installed as modular packages in any fitting machine. A new line of encoders is to be launched with this technology.

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