Application Note

Dynamic Z-Track™ Technology: An Advanced Battery Gauging Algorithm for Dynamic Load Applications

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ABSTRACT

This application note describes a short history of Texas Instruments' battery gauging algorithms, explains challenges in battery gauge operation when load currents have frequent, rapid variations, and details the features and benefits of the Dynamic Z-Track™ algorithm applied to dynamic load current applications.

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Trademarks

Dynamic Z-Track™ and Impedance Track™ are trademarks of Texas Instruments.
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1 Introduction

This application note describes Texas Instruments' Dynamic Z-Track™ algorithm used in the BQ41z50 and other Texas Instruments' battery gauge devices. The gauging algorithm is a successor to the Impedance Track™ gauging algorithm used in many previous TI battery gauge devices such as BQ40z50, BQ27z561, BQ27z746, BQ34z100, and so forth. The Dynamic Z-Track algorithm is designed to enable accurate battery gauging in application environments when the battery load current exhibits frequent and rapid changes over long time periods.

2 Battery Gauging Algorithm Background

Battery gauges provide information needed to characterize a battery pack powering electronic or electro-mechanical systems. Battery gauges estimate the remaining capacity, state of charge, and state of health of a battery cell or pack.

Battery gauges often rely on approximations exploiting the characteristics of the load current to enable accurate battery parameter and state estimation with low computational overhead and power consumption. In systems that traditionally use battery gauges, such as notebook and tablet computers, mobile phones, and other personal electronic equipment, load currents vary slowly and have long idle periods. In these cases, direct measurements of battery voltage during idle periods can be applied to determine battery state of charge. There is a one-to-one mapping between the battery open circuit voltage (OCV) and the state-of-charge (SoC), or equivalently, the degree-of-discharge (DoD), when the battery load current has been idle for a sufficiently long period of time. The curve characterizing the battery resistance normalized to room temperature can be estimated using voltage and current measurements when the load current is constant or slowly varies for long intervals of time.

Trends in electronic device usage, however, are applying battery power to devices and applications with highly dynamic load currents over long time periods. Systems that were previously powered by wired connections and are now often battery powered to provide customers with greater portability and flexibility. Power tools, drones, and cleaning robots are examples of systems that apply battery power in the presence of highly varying load currents. Additionally, traditional applications such as notebook computers are using variable load currents, such as in Dynamic Battery Power Technology (Turbo Mode), to balance computational throughput with system power dissipation. In these applications, the load current includes 10 second pulses of sustained high battery current (SPC) up to two times the battery C-rate and 10ms pulses up to four times the battery C-rate (CPC). Example DBPT load currents are shown in Figure 2-1. Emerging artificial intelligent (AI) applications for notebook and mobile personal electronics, such as classification with neural networks or content generation with large language models (LLMs), also require highly variable load currents drawn from the battery. For these applications, the gauge algorithms cannot rely on approximations designed for stable and slowly varying load currents.

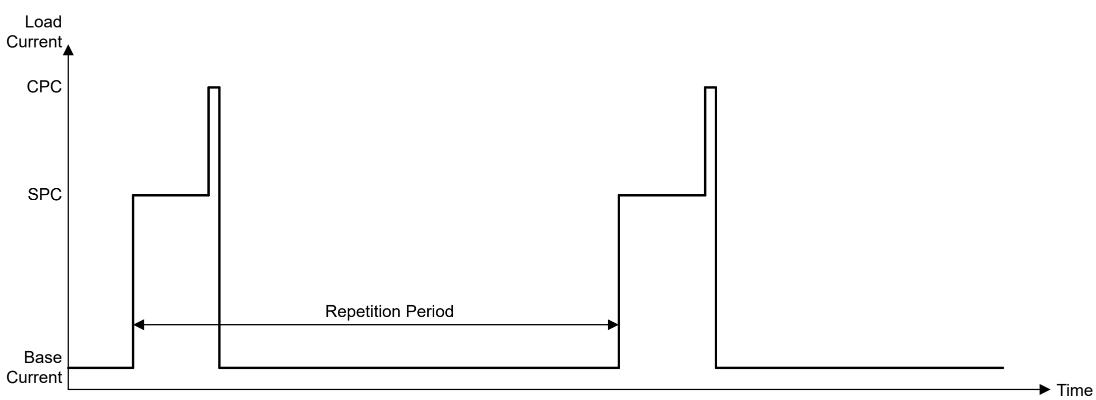

Figure 2-1. Dynamic Battery Power Technology Example Load Current

The next sections of this document describe the approximations used to model batteries for stable load currents, the shortcomings of these models for systems with dynamic load currents, techniques to model battery behavior for dynamic loads, gauging algorithms based on the dynamic models, and impact on the accuracy of remaining capacity and state of charge estimation.

3 Battery Modeling

Many battery gauge algorithms use an equivalent circuit model for the battery to provide the desired information about the battery pack. The battery model used by the gauge algorithm is selected to manage a tradeoff between the accuracy to represent the battery voltage response to expected load currents and the computational complexity involved in estimation of the parameters. The gauge algorithm used by Impedance Track based gauges is optimized for applications with stable load currents. In these cases, there are long periods of time when the battery load does not vary significantly. A model that captures the low-frequency behavior of the battery is sufficient for battery gauging is shown in Figure 3-1. The nodes V_{term} and Gnd represent the positive voltage battery terminal and the battery terminal connected to ground. For a battery pack containing multiple cells or modules in series, only the terminal of the bottom battery in the stack is connected to the system ground. The resistor, R_S, represents the low-frequency battery resistance. The capacitor, C_S, represents toe charge storage of the battery. In a practical battery model, the R_S and C_S parameters depend on the battery conditions such as SoC and environmental conditions such as temperature.

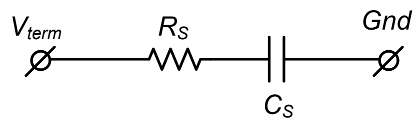

Figure 3-1. Low-Frequency Battery Model

The typical low-frequency battery model includes a resistor to model the effect of the load current on the battery voltage, and a variable capacitor to model the variation of the OCV of the battery as discharged. The OCV is the battery voltage after a long period of time without load current flowing into or out of the battery. Both the OCV and the low-frequency resistance of the battery are functions of the SoC, and the battery cell temperature.

The battery OCV is described as a function of the battery SoC, or equivalently, the DoD. The SoC is a ratio between the remaining charge in the battery and the total chemical charge storage capacity, or Qmax. The value of Qmax is the available charge that can be provided by the battery in the limit of very low discharge current. The OCV versus SOC curves for typical Li-Ion, NMC, and LFP battery chemistries do not shift significantly as the battery ages. Thus, the Qmax parameter captures the effect of battery aging for very low load currents. As the battery ages, the estimated Qmax value decreases, describing the loss of charge storage capacity.

The battery resistance captures the effect of large currents on the battery terminal voltage. For stable or slowly-varying load currents, the difference between the battery OCV and the measured battery voltage is proportional to the load current. The battery gauge maintains a resistance estimate of the battery and the temperature sensitivity as functions of SoC and DoD. For a stable load current, known temperature, and SoC, the battery model can predict the battery terminal voltage.

The initial parameters of the battery model are determined by characterizing a new battery. Since the OCV drifts a small amount versus SoC, this is treated as a fixed parameter of the battery model. The gauge tracks the Qmax and fixed temperature resistance parameters since these change significantly as the battery ages. For typical Li-Ion and related battery chemistries, the battery is considered at the end of useful life when the Qmax has declined to 80% of the original value.

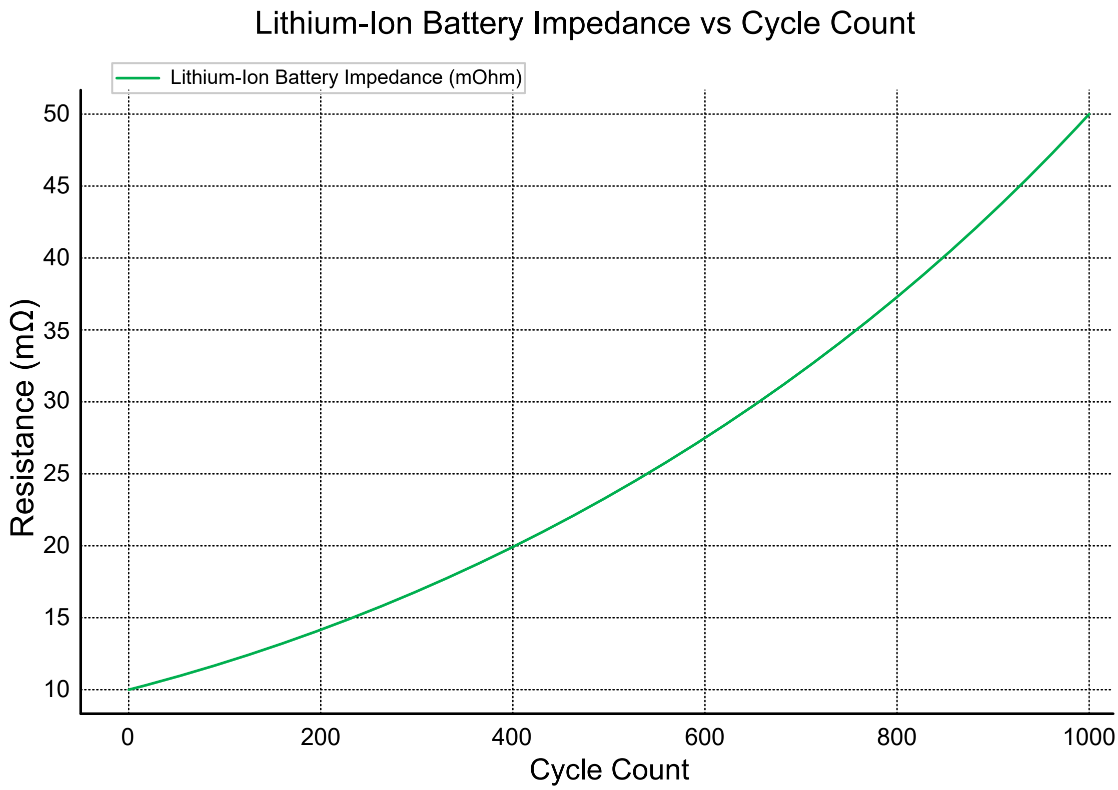

Figure 3-2. Battery Resistance vs. Age

The low-frequency resistance of the battery increases significantly with age, depending on the battery chemistry and usage as shown in Figure 3-2. Over 100 cycles, a typical value of the low-frequency resistance of the battery can increase by 60%, depending on the battery chemistry and usage patterns.

For stable load currents, modeling the battery impedance by a single resistor leads to a reasonable tradeoff between the computational complexity of estimating the model parameters and the accuracy of the gauge predictions of SoC and the remaining capacity of the battery.

The battery SoC in Impedance Track based gauges is estimated from either a voltage measurement or a current measurement, depending on the recent behavior of the load current. When the load current has been near zero for a sufficiently long period of time, the battery voltage matches the OCV. Since the OCV versus SoC curve is monotonic, the voltage measurement can be mapped to an estimate of SoC. When the battery is charging or discharging, the battery voltage does not map to the correct SOC value due to the effect of the battery impedance. To reduce the computational complexity of the gauging algorithm, the SoC is estimated using the ratio between the integrated current and the battery Qmax when current is flowing

4 Battery State of Charge Estimation and Remaining Capacity Prediction

With properly estimated Qmax and battery impedance parameters, the gauge can predict the remaining charge in the battery pack for a variety of load currents as shown in Figure 4-1. The challenge in this prediction is to estimate the difference between the battery OCV and the output voltage across the battery terminals due to the load current and battery impedance. For the purpose of this prediction, the gauge assumes that there is a minimum voltage needed to successfully operate the overall electronic system connected to the battery pack. The prediction of the battery capacity is the difference between the most recent SoC estimate, and the SoC when the battery terminal voltage is predicted to reach the minimum voltage for system operation. The value of Qmax is equal to the battery capacity in the limit of very small discharge current, when the IR voltage drop is negligible. The remaining capacity of the battery is the difference between the total capacity estimate shown in Figure 4-1 and the estimate of the battery DoD.

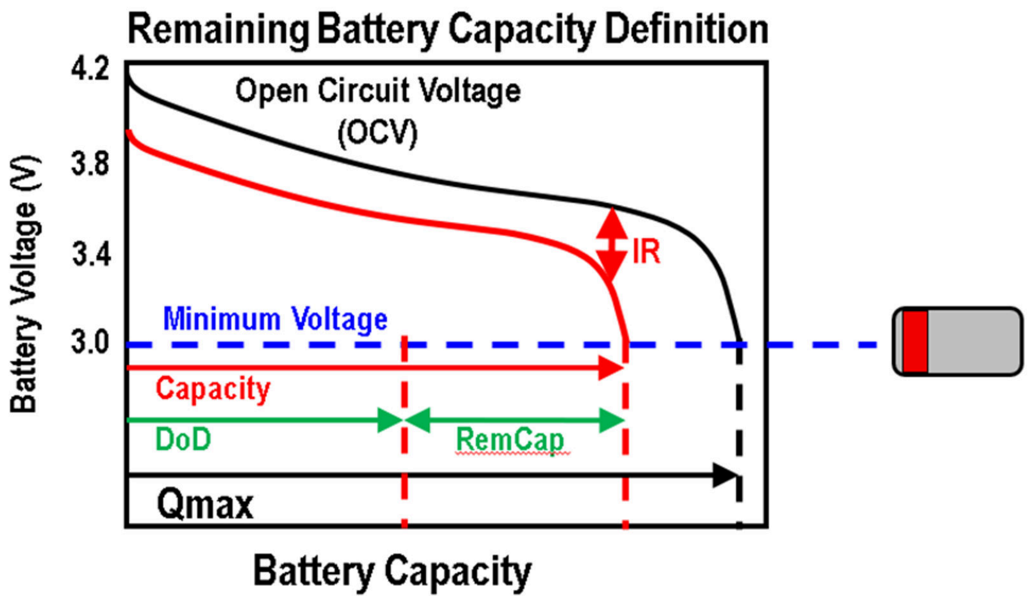

Figure 4-1. Remaining Capacity Prediction

The remaining capacity prediction depends strongly on the load current and resistance. The IR voltage drop across the internal battery resistance makes the amount of charge that can be provided by the battery a function of the load current. For larger currents, the battery terminal voltage reaches the minimum value sooner.

Gauge algorithms that use only voltage measurements without compensation for the IR drop do not capture this effect and produce inaccurate estimates of the remaining battery capacity. Additionally, gauge algorithms that do not estimate the increasing battery resistance with age can underestimate the IR voltage drop. This generates inaccurate estimates of the remaining capacity.

5 Challenges Modeling Battery Response to Dynamic Load Currents

The resistor and capacitor battery model captures significant aspects of the battery behavior versus age and load current level using a simple equivalent circuit. The equivalent circuit captures the battery behavior well when load currents are stable, and transient voltage responses settle. In practice, batteries exhibit voltage transient responses with significant duration in response to changes in load current.

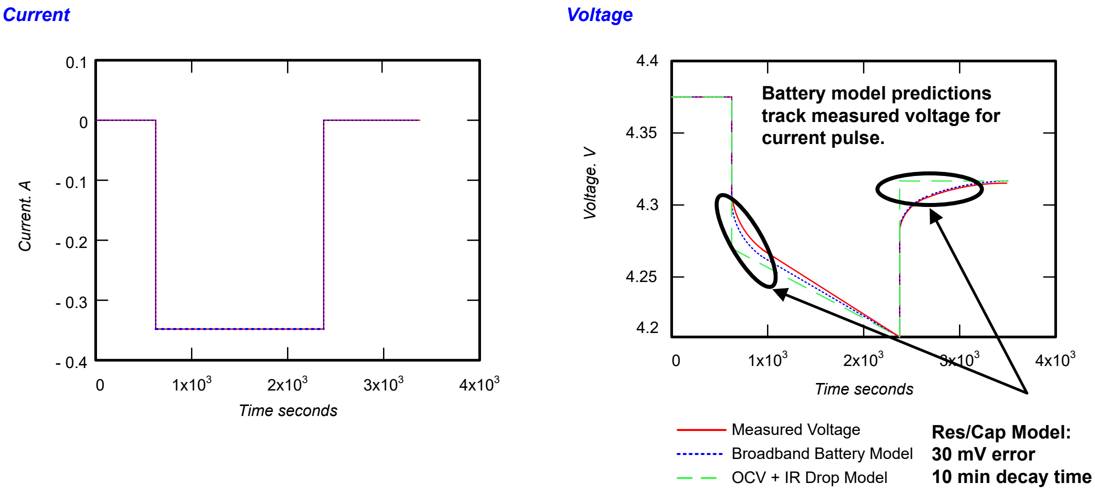

Figure 5-1. Battery Transient Response

As seen in Figure 5-1, the battery voltage transient can require more than 10 minutes to settle in response to a C/2 step in load current. After the relaxation time has passed, the resistor and capacitor battery model generates an accurate prediction of the battery terminal voltage. After the relaxation time, the battery resistance model can be updated accurately since the difference between OCV and battery terminal voltage is equal to the IR drop predicted by the model. Traditional gauge algorithms, such as the Impedance Track algorithm, do not update the resistance model unless the load current is stable enough for this settling to occur.

6 Approaches to Deal with Battery Dynamics

Bypass

In a battery gauge based on the resistor and capacitor equivalent circuit, the gauge relies on a resistance model measured for a new battery or updates the resistance model when the load current is stable for a long enough time that the battery transients settle. When the battery load is highly dynamic, intervals of stable current long enough to verify transient settling are not frequent enough to enable accurate tracking of the resistance increase as the battery ages. In these applications, gauges based on the resistor and capacitor equivalent circuit underestimate the resistance of the battery. In these situations, the IR drop is underestimated, so the gauge overestimates the remaining capacity of the battery. In this situation, the overall system can need to shut down prematurely, and the terminal voltage can approach the minimum value faster than the gauge predicts.

However, in applications where there are frequent intervals of stable load current sufficient to allow the battery transient response to settle, traditional gauging algorithms are able to track the increasing resistance of the battery and provide accurate predictions of battery remaining capacity.

Broadband Battery Modeling

An alternative approach to using a resistor or capacitor equivalent circuit with selective updating is to use a more accurate broadband model of the battery. As shown in Figure 4-1, a broadband battery model can provide accurate predictions of the battery terminal voltage during the transient response relaxation interval. A properly designed broadband battery model can generate the transient response accurately for arbitrary load current conditions, not just step responses.

Dynamic Z-Track™

The Dynamic Z-Track algorithm relies on a broadband model of the battery response that can generate accurate battery terminal voltage estimates for dynamic load currents over long time periods. The Dynamic Z-Track is parameterized by the same values as Impedance Track based gauges: the battery resistance normalized to room temperature versus DoD and maximum battery charge storage (Qmax). The Dynamic Z-Track algorithm uses a correction factor to the IR drop in the simple resistor and capacitor battery equivalent circuit to generate accurate battery terminal voltage predictions and battery resistance estimates. The Qmax parameter is estimated using the same techniques as Impedance Track based gauges.

6.1 Benefits to Gauging Accuracy for Dynamic Loads

There are two benefits to using a broadband model in battery gauging. First, the model can be used to enable battery resistance estimation in situations where the battery terminal voltage has not fully settled. The broadband model can prevent inaccurate IR voltage drop due to dynamic load current. The variation of the resistance with aging can be tracked regardless of the load current characteristics, so remaining battery capacity can be predicted correctly for applications with dynamic load currents. Second, the model can be used to more accurately predict the battery terminal voltage, accounting for the transient response.

6.2 Algorithm Performance

The Dynamic Z-Track algorithm enables improved resistance estimation and remaining capacity prediction for dynamic load applications. A comparison algorithm to quantify the improvement in remaining capacity is a compensated end of discharge voltage (CEDV) gauge algorithm. This algorithm uses compensation of the IR drop estimated from a new battery to predict the location when the battery terminal voltage reaches the end of discharge. The Dynamic Z-Track algorithm is able to track the resistance accurately to within a small error tolerance. For an aged battery, the resistance can increase by more than 50% near the end of the battery discharge, and a CEDV gauge underestimates the voltage drop due to load current.

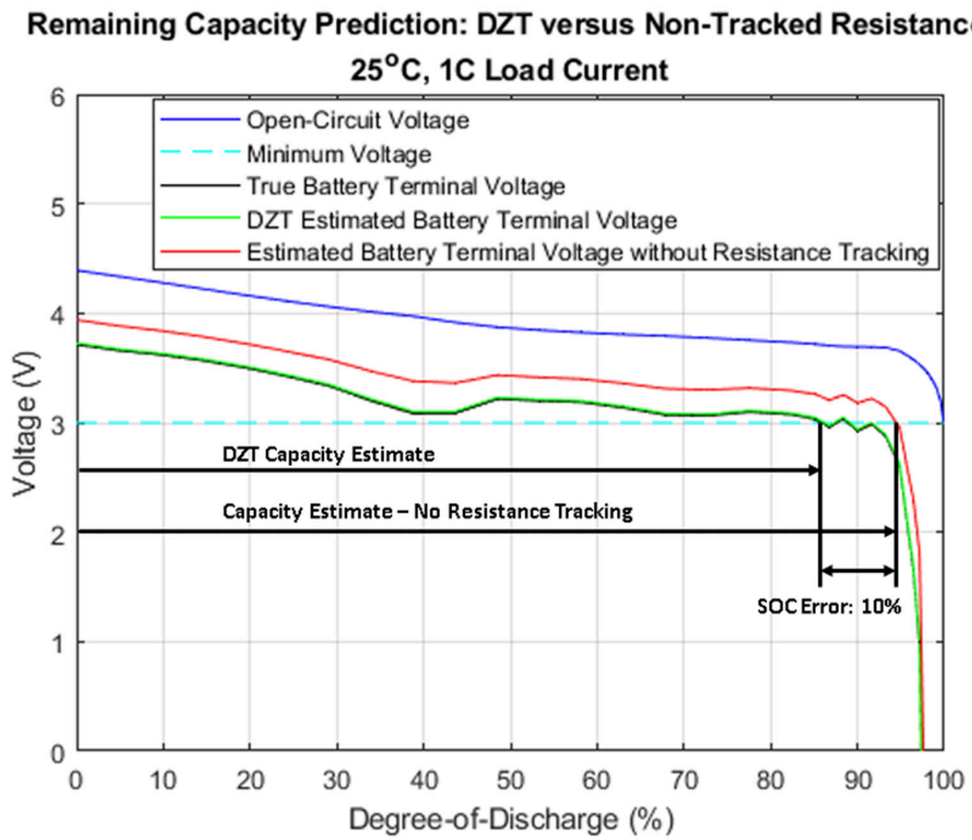

Figure 6-1. Remaining Capacity Estimation Comparison: Dynamic Z-Track™ vs. No Resistance Update, 1C Load

The effect of the gauging algorithms on remaining capacity prediction is shown in Figure 6-1. The Dynamic Z-Track algorithm is able to track the resistance accurately as the battery ages, with a small error tolerance. The CEDV algorithm under-estimates the resistance of the aged battery significantly. For a 1C load shown in Figure 6-1, the Dynamic Z-Track algorithm predicts the SOC when the battery voltage reaches the minimum 3V threshold accurately. The CEDV algorithm does not predict the SOC when the voltage reaches 3V accurately. The algorithm has a 10% over-estimation of the battery remaining capacity versus Dynamic Z-Track. At higher load currents, the IR drop is more significant, so the remaining capacity error in CEDV is larger. For the test case shown, the overestimation error for a 1.75 C average load current is 60%, as seen in Figure 6-2.

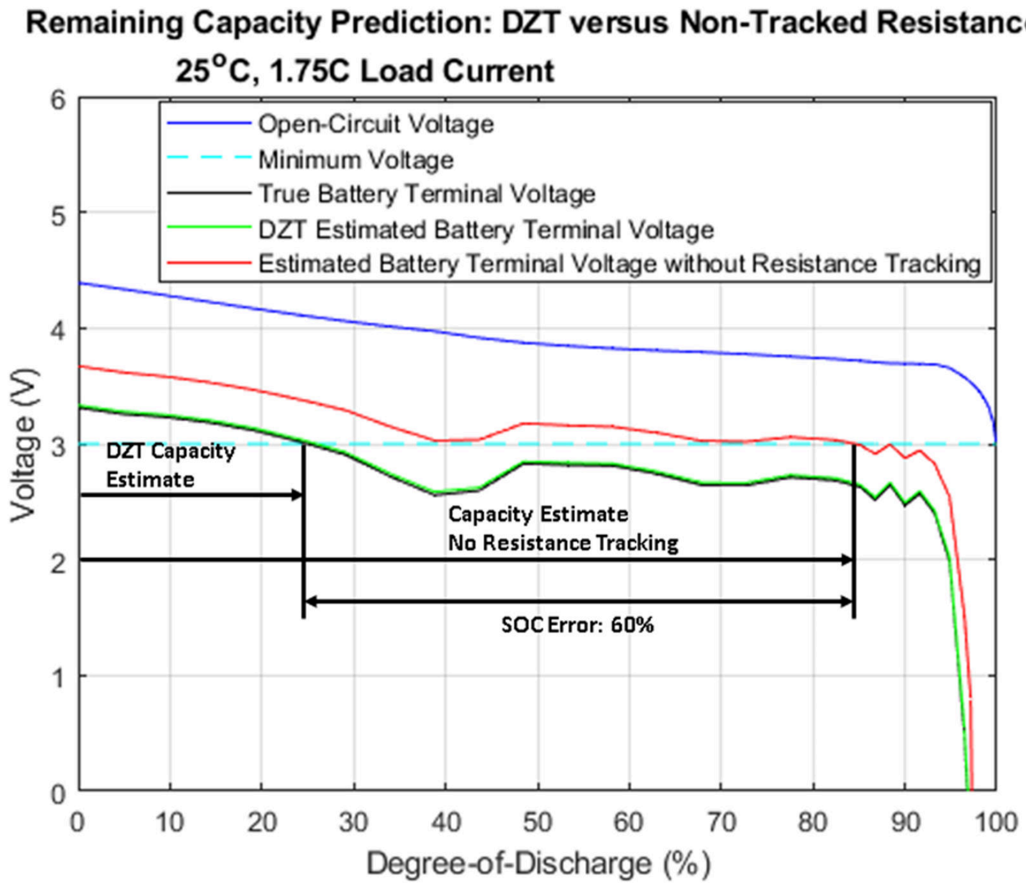

Figure 6-2. Remaining Capacity Estimation Comparison: Dynamic Z-Track™ vs. No Resistance Update, 1.75 C Load

The expected improvement in SOC accuracy depends on the battery behavior as the battery ages, and the details of the load current during discharge. For some load currents, there are frequent and long intervals of stable load current, so that an Impedance-Track based gauge algorithm can achieve similar performance to Dynamic Z-Track. A battery with a long lifetime shows a slow increase in resistance. The gap between Dynamic Z-Track and fixed-resistance estimates of remaining capacity is small until the battery ages enough that the resistance shows a significant increase.

Batteries that show rapid increase in resistance can have even larger errors in SOC estimation with dynamic loads than the example in Figure 6-2.

7 Summary

The Dynamic Z-Track gauging algorithm enables more accurate estimation of the battery resistance and remaining capacity for applications with dynamic load currents. The Dynamic Z-Track relies on a broadband battery model that compensates for battery relaxation in the resistance estimation portion of the gauging algorithm. Accurate tracking of the battery resistance throughout the life cycle enables accurate remaining capacity prediction of the instant when the battery terminal voltage reaches the minimum value for operation of the battery-powered system. The Dynamic Z-Track enhances gauging performance for a wide range of applications such as drones, robots, power tools, and AI-enhanced portable electronics.

A comparison of the performance of Dynamic Z-Track and Impedance Track for stable and dynamic loads is shown in Table 7-1. To determine if a system benefits from Dynamic Z-Track, reach out to a TI representative.

Table 7-1. Comparison of Dynamic Z-Track™ and Impedance Track™

Load	Dynamic Z-Track™			Impedance Track™			CEDV		
	Resistance estimation	State of health	RemCap	Resistance estimation	State of health	RemCap	Resistance estimation	State of health	RemCap
Stable	Accurate	Yes	Yes	Accurate	Yes	Yes	Fixed at new cell value	Accuracy declines with age	Accuracy declines with age
Pulsed	<10% worst-case error vs. SOC and T	Yes	Yes	<100% worst-case error vs. SOC and T	Possible for constrained current pulse shape	No	<100% worst-case error vs. SOC and T	Possible for constrained current pulse shape	No

8 References

- Texas Instruments, Impedance Track™ Gauge Configuration for Dynamic Loads (EPOS), application note
- Texas Instruments, Theory and Implementation of Impedance Track™ Battery Fuel-Gauging Algorithm in bq2750x Family, application note
- Texas Instruments, Impedance Track™ Gas Gauge for Novices, application note

9 Revision History

NOTE: Page numbers for previous revisions may differ from page numbers in the current version.

Changes from Revision * (May 2025) to Revision A (July 2025)	**Page**
• Updated all instances of IT and DZT to Impedance Track and Dynamic Z-Track	1