

# BAT-GPT: Large Language Models for Interactive Digital Twin-based BMS

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**Abstract**—This study introduces BAT-GPT, a novel digital twin assistant leveraging T5 architecture for battery management systems (BMS). Using a dataset derived from NASA’s battery data, BAT-GPT processes digital twin insights effectively without fine-tuning. Employing gradient accumulation significantly enhances performance metrics, improving explainability and interaction within BMS digital twins.

**Index Terms**—BMS, digital twin, large language models, battery management systems

## I. INTRODUCTION

Effective management of battery systems is crucial for improving their safety, performance, and lifespan. Integrating the Internet of Things (IoT) and digital twins has significantly transformed battery management systems (BMS). Digital twins, as virtual replicas of physical systems, utilize IoT-generated sensor data, artificial intelligence algorithms, and sometimes physics models to offer real-time monitoring, diagnostics, and predictive maintenance [1].

Several studies have shown the effectiveness of digital twins in BMS. Cloud-based systems [1] and state estimation models [2] demonstrate the ability of digital twins to enhance battery management through extensive data analysis and real-time operational insights. However, the vast and complex data of digital twins presents several challenges. This data, often high-dimensional, requires substantial domain knowledge to interpret and could be more user-friendly for non-experts needing to make informed decisions [3]. Additionally, the complexity of digital twin outputs hampers the urgency required in BMS decision-making, complicating the translation of predictive outputs into understandable and actionable insights. Recent advancements in large language models (LLMs) have brought significant potential to the digital twin domain. The T5 model, for example, has opened up new avenues for enhancing the interactivity and accessibility of BMS through digital twin assistants by transforming complex data into comprehensible information [4].

This study introduces BAT-GPT, a novel digital twin assistant that utilizes the T5 model to bridge the gap between complex data and actionable insights in BMS. BAT-GPT is specifically designed to interpret digital twin outputs and enhance user interaction by providing informed responses. To train BAT-GPT effectively, we developed a custom dataset comprising prompts and responses based on a NASA battery dataset. This approach allowed BAT-GPT to generate user-friendly and insightful responses directly from the model predictions.

## II. PROPOSED SYSTEM

### A. Problem formulation

We proposed assistant, as illustrated in Fig. 1, is based on two components:

- 1) **Capacity Prediction with LSTM:** The battery’s capacity  $C_{\text{pred}}$  is predicted using an LSTM model as:

$$C_{\text{pred},t} = \text{LSTM}(\mathbf{X}_t, h_{t-1}, c_{t-1}), \quad (1)$$

where  $\mathbf{X}_t$  includes time-dependent inputs like voltage, and  $h_{t-1}, c_{t-1}$  are the previous hidden and cell states.

- 2) **Advisory Generation with T5:** Advisories  $A$  are generated based on the predicted capacity using a T5-based model, BAT-GPT:

$$A = g_{\text{T5}}(C_{\text{pred}}, I), \quad (2)$$

where  $I$  represents input prompts.

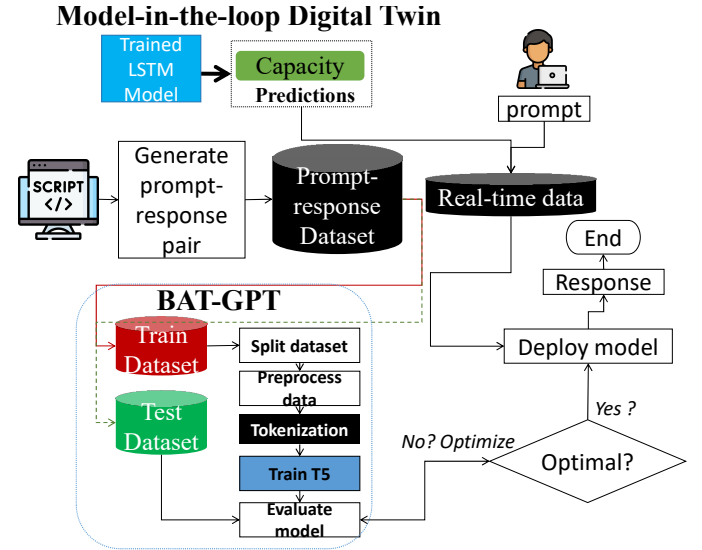


Fig. 1. Model implementation flowchart, illustrating how the BAT-GPT model processes inputs to generate outputs.

### B. Optimization Objectives

The BAT-GPT model minimizes negative log-likelihood (NLL) for enhancing text accuracy:

$$L = - \sum_{t=1}^T \log(p_{y_t}), \quad (3)$$

with  $p_{y_t}$  being the probability for the true token  $y_t$  at position  $t$ .

### C. Gradient Accumulation Strategy

To handle larger batch sizes, gradient accumulation is applied:

$$\Delta w = \frac{1}{N} \sum_{i=1}^N \nabla L_i(w), \quad (4)$$

where  $\Delta w$  updates model weights,  $N$  is the number of mini-batches, and  $\nabla L_i(w)$  is the gradient of the loss for the  $i$ -th mini-batch. This method optimizes GPU resources and enhances computational efficiency.

### D. Implementation approach

The training dataset for the LSTM model is derived from the NASA battery dataset [5], which is also used to generate prompt-response pairs for the BAT-GPT model. Each dataset entry includes a prompt crafted from voltage, current, and temperature data ( $\mathbf{X}$ ) and a response based on the battery capacity ( $\mathbf{y}$ ) at that time. This methodology ensures that the model simulates realistic BMS scenarios. Fig. 1 outlines the data processing workflow where text inputs are tokenized into IDs. The dataset is segmented into 90% training, 10% validation, and 10% testing proportions. BAT-GPT processes this data using the T5 model's pre-trained parameters, optimizing output generation without the need for fine-tuning, thus maximizing the efficiency of computational resources.

## III. RESULTS AND DISCUSSION

The BAT-GPT model was evaluated on a dataset with 8,934 samples using metrics like loss and time. Trained on an Intel i9-10940X with 64 GB RAM and 130 GB memory, the BAT-GPT model underwent training at learning rates of  $10 \times 10^{-5}$ , weight decay of 0.01, and used 16 gradient accumulation steps. Fig. 2 and Fig. 3 illustrate losses and training durations, showing models with gradient accumulation perform better, reducing training time by 5%.

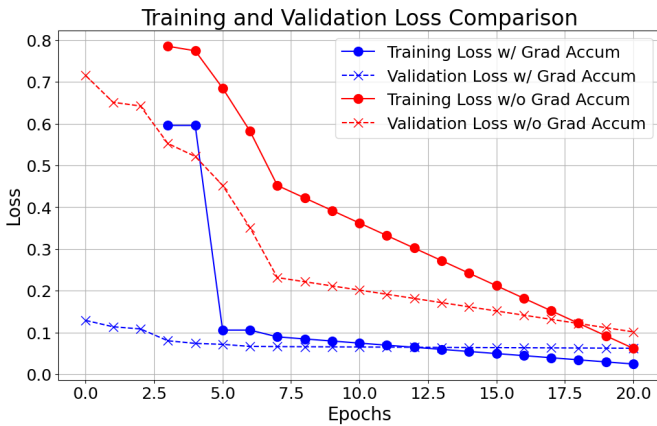


Fig. 2. Training and validation loss results on BAT-GPT with and without gradient accumulation, highlighting the effect of this strategy on the model performance.

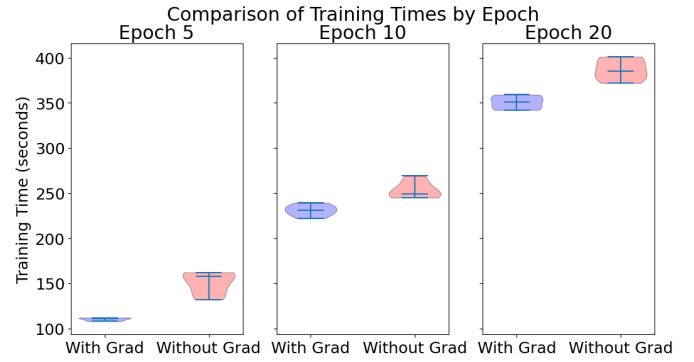


Fig. 3. Training time results on BAT-GPT with and without gradient accumulation, highlighting the effect of this strategy on the computation time.

## IV. CONCLUSION

This study introduced BAT-GPT, a T5-based digital twin assistant for BMS, transforming complex data into actionable insights with significant accuracy, leveraging a comprehensive NASA battery dataset. Future work will focus on integrating more contextual data.

## ACKNOWLEDGMENT

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