# Prediction of Time-Series Discharge Characteristics of Primary Batteries for IoT Device Using Machine Learning

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## Abstract

*Efforts are made to construct a prediction model for the discharge characteristics of IoT device batteries using time-series prediction models based on Transformers. With the aim of calculating SOC (State of Charge) through recursive prediction, conditions and processes conducive to more accurate recursive prediction were investigated. Currently, recursive prediction with iTransformer tend to be good score. It was also suggested that adding noise during recursive prediction may enable more stable long-term predictions.*

**Keywords:** IoT device; primary battery; SOC; Transformer; PatchTST; Non-stationary Transformers; iTransformer

## 1. Introduction

IoT devices often use primary batteries from the viewpoint of cost and stability. To ensure the stable operation of IoT systems, it is crucial to accurately assess the battery status of IoT devices. In our work, we proposed a method for high-precision state prediction of primary batteries for IoT devices, combining estimated device's current integration based on the operation task and the Recursive Least Squares (RLS) method [1]. The RLS method requires data measurement in advance to create a battery model, which lead to high implementation costs. To address this problem, we are attempting to predict battery status using machine learning only from battery operating data without prior battery data acquisition. Previous our research [2] has shown that when using PatchTST [3], a derived model of Transformer [4], the accuracy of predicting battery voltage one step ahead is equivalent to or better than the RLS method. On the other hand, there remained issues with the feasibility of calculating the predicted SOC for multiple steps ahead. The recursive prediction did not work. Fig 1 shows an example of a multi-step prediction with PatchTST (input sequence length 30, prediction length 54, input variables are terminal voltage and estimated Coulomb amount). Predicted waveform stops moving before reaching the IoT device's terminal voltage of 2.4V.

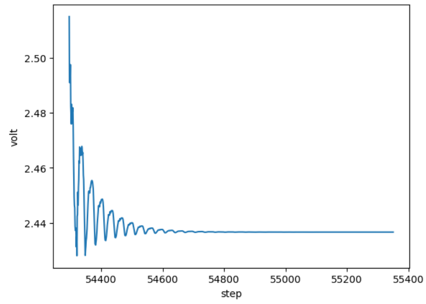


Fig. 1. Multi-step prediction example (PatchTST)

This paper investigated the conditions for realizing SOC calculation by recursive multi-step prediction by taking new approach, such as new Transformer-based models, data input conditions, and processing during recursive prediction.

## 2. Data

Operational data that can be obtained from the IoT devices used in our research include battery voltage, temperature, and the estimated coulombs amount consumed by the device [1].

Fig 2 shows the battery voltage data used in this study. This is the discharge characteristic under indoor natural fluctuation conditions (6°C to 29°C), and the voltage is acquired once every step (60 seconds). From this Fig, as the discharge progresses, the voltage decreases, and the variation increases. In other words, this data is highly non-stationary.

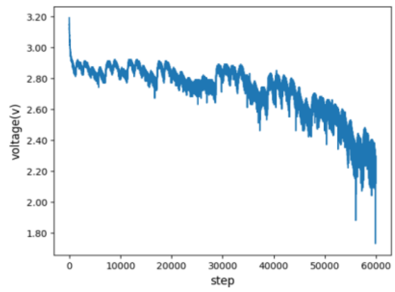


Fig. 2. battery discharge characteristic of IoT device

Fig.3 is a diagram showing the discharge characteristics and temperature in an area of about

2000 steps. This Fig suggests that there is a correlation between voltage and temperature in a certain long-term step.

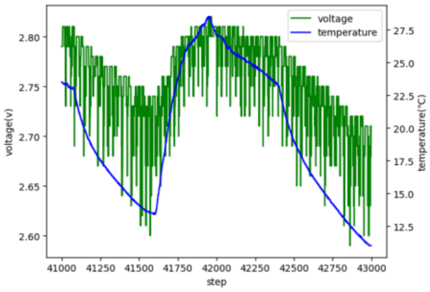


Fig. 3. voltage and temperature in 2000step area

## 3. Time-series prediction model

In this study, the following time series prediction models were constructed for battery discharge characteristics prediction. New models have been introduced to address non-stationarity and correlation between variables more effectively.

1. PatchTST: It is the model that showed the best score for predicting one step ahead in previous research. Adopted as a base model. This model features splitting time series data into separate sequences, inputting each segment into a Transformer Encoder with patching it.
2. Non-stationary Transformers [5]: A model based on Transformer that has been modified to deal with non-stationarity in time series data. Series Stationarization performs normalization for each time series input unit and denormalizes it at the output to deal with non-stationarity. De-stationary attention is introduced to restore excessive stationarity.
3. iTransformer [6]: A newly proposed model that better considers the correlation between multiple variables. iTransformer regards independent time series as variate tokens to capture multivariate correlations by attention unlike traditional Transformer and utilize layernorm and feed-forward networks to learn series representations. There is also a mention that variables are normalized in layernorm.

## 4. Recursive prediction

To perform SOC calculation, recursive prediction was performed for the time series model in Section 3 using the voltage prediction results as a new sequence voltage input, while changing the input sequence length and prediction length several times. Train and Valid for each model were performed on operating data up to an estimated SOC of 20% (calculated from the estimated coulomb account and the nominal capacity of the primary battery). The prediction started from the estimated SOC 20%. Voltage, temperature, and estimated coulombs amount are adapted as input variables. They were constructed with and without temperature inclusion.

The voltage utilizes the preceding predicted value as the new sequence input, whereas the estimated coulomb amount employs the calculated value. Once the operational conditions of the IoT device are determined, the forthcoming coulomb value can be computed. As for the temperature, we presumed that it would be feasible to acquire the temperature in the future through various means (e.g., via a weather forecast, etc.). In this study, the actual temperature was employed as input.

Fig. 4 shows the first recursive prediction output of each model with input sequence length 96 and prediction length 96. Input variables are voltage, temperature, and estimated coulombs. The horizontal axis is step, and the vertical axis is normalized voltage value. Prediction waveforms 0 to 96 steps are the values in which the previous prediction result is input as recursive prediction, and the 97 to 192 steps are the predicted outputs. Fig. 5 shows the results of the 5th recursive prediction. In the 5th recursive prediction (576 steps ahead), although a little oscillations remain in the Non-stationary Transformers, the oscillations in the predicted waveform have attenuated and almost disappeared.

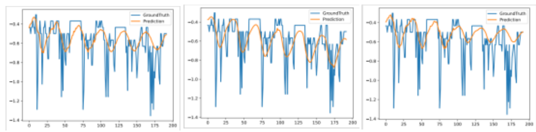

Fig. 4. 1st recursive prediction (left:PatchTST center:Non-stationary Transformers right: iTransformer)

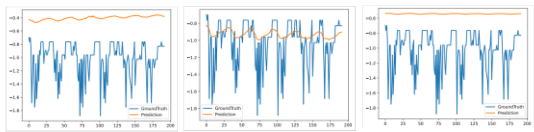

Fig. 5. 5th recursive prediction (left:PatchTST center:Non-stationary Transformers right: iTransformer)

From this result, stable multi-step prediction over long steps ahead could not be expected just by considering non-stationarity and correlation with temperature. Here, we attempted to introduce a process to add noise to input sequence voltage during recursive prediction, although it was a bit tricky. This idea comes from that the predicted waveform output reproduces the periodicity and trends of time-series data and appears to be little free of noise components included in the training data, resulting in deviation from the training data. The applied noise was created so that the average value was 0 and the variance value of the difference between the first predicted value and the actual value was the same.

Fig 6 shows the 5th recursive prediction results when noise is added. By applying noise, the attenuation of the oscillations of the 5th recursive prediction output is relaxed and remains. Since there may be a possibility for stable predictions over a longer step ahead. We treated it as a processing condition and proceed with the evaluation.

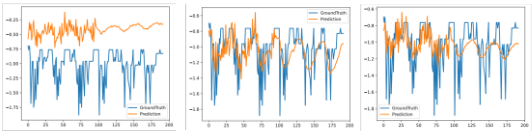

Fig. 6. 5th recursive prediction with noise (left:PatchTST center:Non-stationary Transformers right: iTransformer)

## 5. Evaluation results

Table 1 shows result of RMSE and calculated SOC error by recursive predictions in test data. In the case where the predicted voltage reaches termination voltage of 2.4V, the SOC error ratio is calculated, otherwise filled in with NA. The steps to the termination voltage in test data are approximately 8000 steps.

**Table 1: RMSE and calculated SOC error in test data**

| model/ include temperature in input variables/ add noise/ sequence length/ prediction length | RMSE | *calculated SOC error(%)* |
|---|---|---|
| PatchTST/no/no/96/96 | 0.133 | NA |
| PatchTST/yes/no/96/96 | 0.062 | NA |
| PatchTST/no/yes/96/96 | 0.472 | NA |
| PatchTST/yes/yes/96/96 | 0.116 | NA |
| PatchTST/no/no/332/332 | 0.058 | NA |
| PatchTST/yes/no/332/332 | 2.191 | 15.16 |
| PatchTST/no/yes/332/332 | 0.129 | 3.76 |
| PatchTST/yes/yes/332/332 | 0.063 | NA |
| PatchTST/no/no/720/720 | 0.074 | NA |
| PatchTST/yes/no/720/720 | 0.095 | NA |
| PatchTST/no/yes/720/720 | 0.142 | NA |
| PatchTST/yes/yes/720/720 | 0.112 | -1.28 |
| Non-stationary Transformers/no/no/96/96 | 0.131 | NA |
| Non-stationary Transformers/yes/no/96/96 | 0.054 | NA |
| Non-stationary Transformers/no/yes/96/96 | 0.208 | NA |
| Non-stationary Transformers/yes/yes/96/96 | 0.587 | NA |
| Non-stationary Transformers/no/no/332/332 | 0.067 | NA |
| Non-stationary Transformers/yes/no/332/332 | 0.115 | NA |
| Non-stationary Transformers/no/yes/332/332 | 1.807 | -4.5 |
| Non-stationary Transformers/yes/yes/332/332 | 5.410 | NA |
| Non-stationary Transformers/no/no/720/720 | 0.117 | NA |
| Non-stationary Transformers/yes/no/720/720 | 0.0653 | NA |
| Non-stationary Transformers/no/yes/720/720 | 0.119 | NA |
| Non-stationary Transformers/yes/yes/720/720 | 0.115 | NA |
| iTransformer/no/no/96/96 | 0.092 | NA |
| iTransformer/yes/no/96/96 | 0.087 | NA |
| iTransformer/no/yes/96/96 | 0.054 | -4.78 |
| iTransformer/yes/yes/96/96 | 0.146 | 5.34 |
| iTransformer/no/no/332/332 | 0.056 | NA |
| iTransformer/yes/no/332/332 | 0.054 | NA |
| iTransformer/no/yes/332/332 | 0.106 | 1.63 |
| iTransformer/yes/yes/332/332 | 0.110 | 1.05 |
| iTransformer/no/no/720/720 | 0.055 | NA |
| iTransformer/yes/no/720/720 | 0.059 | NA |
| iTransformer/no/yes/720/720 | 0.080 | NA |
| iTransformer/yes/yes/720/720 | 0.057 | NA |

The overall trend is that prediction models made by iTransformer tend to have good scores in terms of RMSE and calculated SOC error. It can also be seen that when noise is added, there are many cases where the predicted voltage is reached to termination voltage. Fig 7 shows the waveforms for the following conditions:"iTransformer/no/no/332/332", "iTransformer/yes/no/332/332","iTransformer/no/yes/332/332", and "iTransformer/yes/yes/332/332". In the condition without added noise, the recursively predicted waveform becomes a constant value midway through. In contrast, when noise is added, the waveform continues to oscillate and eventually reaches the terminal voltage. This suggests that adding noise contributes to more stable long-term prediction.

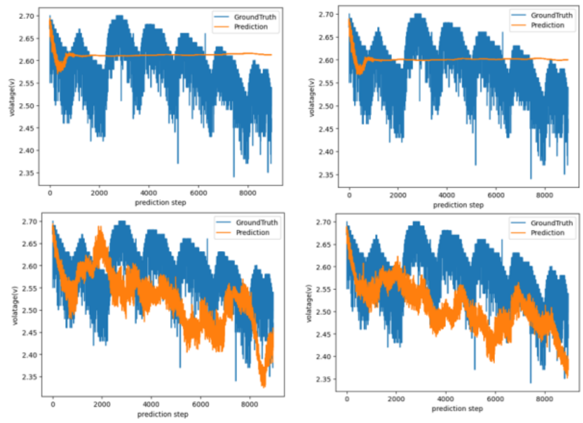


Fig. 7. Recursive prediction in test data (top left: "iTransformer/no/no/332/332" condition, top right: "iTransformer/yes/no/332/332" condition, bottom left: "iTransformer/no/yes/332/332"

condition, bottom right: "iTransformer/yes/yes/332/332" condition)

Regarding the effect of temperature in input variables, there does not seem to be much difference from the results in Fig 7 with sequence length and prediction length of 332. Fig 8 shows the waveforms of "iTransformer/no/yes/720/720" condition and "iTransformer/yes/yes/720/720" condition. In the comparison at a length of 720, it seems that the predicted waveform follows the ground truth more closely when temperature is included. However, the effect of temperature requires further verification with additional data.

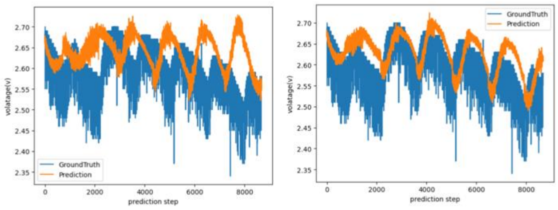


Fig. 8. Recursive prediction in test data (left: "iTransformer/no/yes/720/720" condition, right: "iTransformer/yes/yes/720/720" condition)

## 6. Conclusion

From investigation of the conditions to calculate the primary battery SOC of IoT devices using recursive prediction, the prediction model by iTransformer currently tends to have good scores. It was also suggested that adding noise during recursive prediction may make it easier to reach the terminal voltage.

Future work is planned to investigate the effects of relearning and difference of learning data region. Data patterns other than noise (for example, introduction of time-series data by a generation AI model) will also be considered for processing during recursive prediction. We will also check the results when applied to other sample data and search for more appropriate conditions.

## References

[1] S. Matsushita, H. Shioura, and M. Fukui, "High-Precision Primary Battery Level Estimation Method for IoT Devices,", IEICE (Japanese Edition) Vol.J104-B No.7 pp.589-591. June 2021

[2] S. Matsushita, M. Fukui, K.Takaba, "Time series prediction of primary battery discharge characteristics for IoT devices using machine learning", IEICE (Japanese Edition) Vol.J107-B No.7 July 2024

[3] Y.Nie, N.H. Nguyen, P. Sinthong, J. Kalagnanam, "A Time Series is Worth 64 Words: Long-term Forecasting with Transformers", International Conference on Learning Representations, 2023

[4] A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, I. Polosukhin, "Attention is all you need", Advances in Neural Information Processing Systems (NeurIPS), 5999–6009, 2017.

[5] Y. Liu, H. Wu, J. Wang, M. Long, "Non-stationary Transformers: Exploring the Stationarity in Time Series Forecasting", Advances in Neural Information Processing Systems, 2022

[6] Y. Liu, T. Hu, H. Zhang, H. Wu, S. Wang, L. Ma, M. Long,"iTransformer: Inverted Transformers Are Effective for Time Series Forecasting", arXiv:2310.06625, 2023