

Integrating Model-Based Projection with Data-Driven Correction for Prognostics of All-Solid-State Battery-Supercapacitor Hybrid Devices

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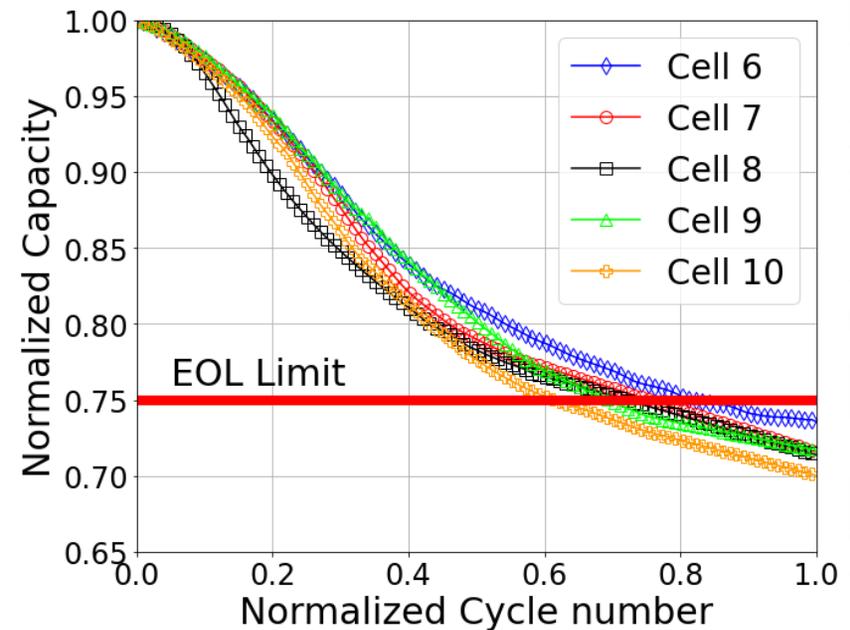
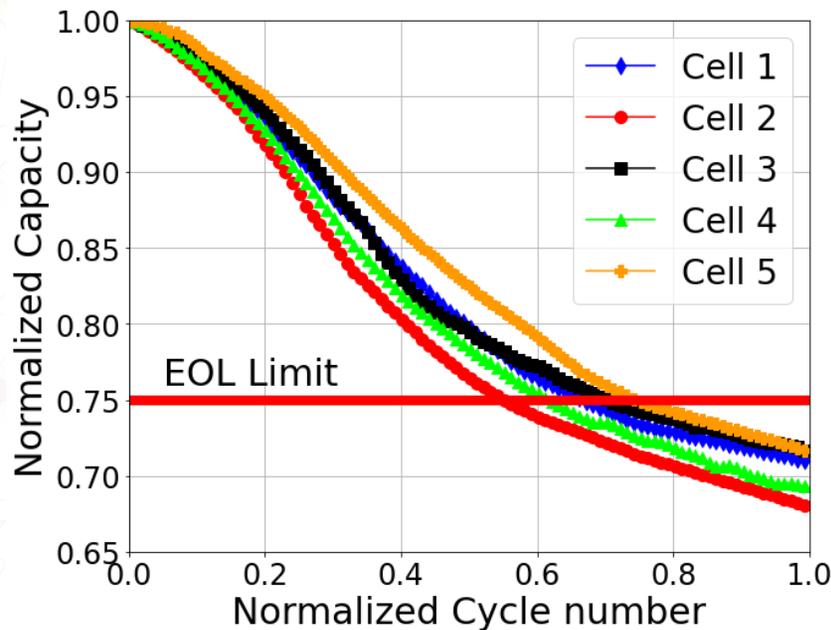
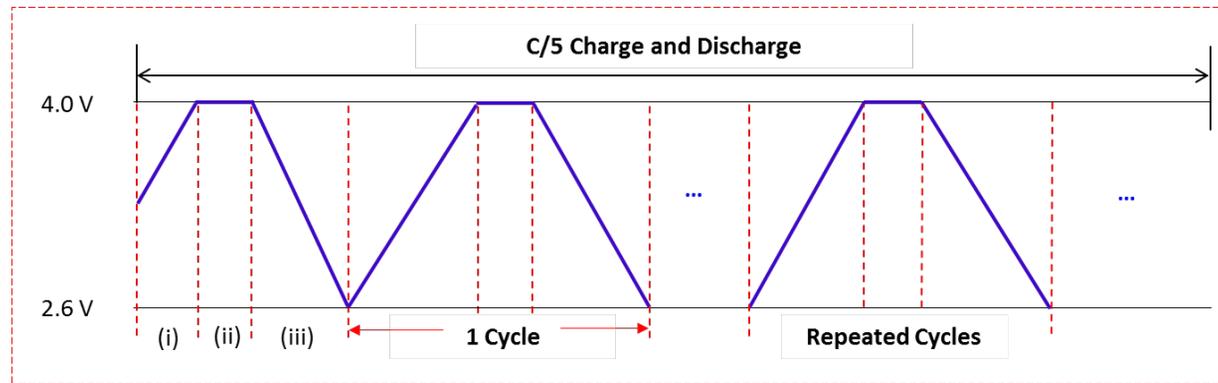
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⁴ Aviation and Missile Center, US Army Combat Capabilities Development Command, Redstone Arsenal, AL 35898, USA

Overview

- Introduction to the battery aging tests
- What is remaining useful life (RUL)?
- Comparison of current RUL prediction methods
- RUL prediction with Gaussian Process
- Data-driven error correction
- Results and Discussion
- Conclusions and Future work

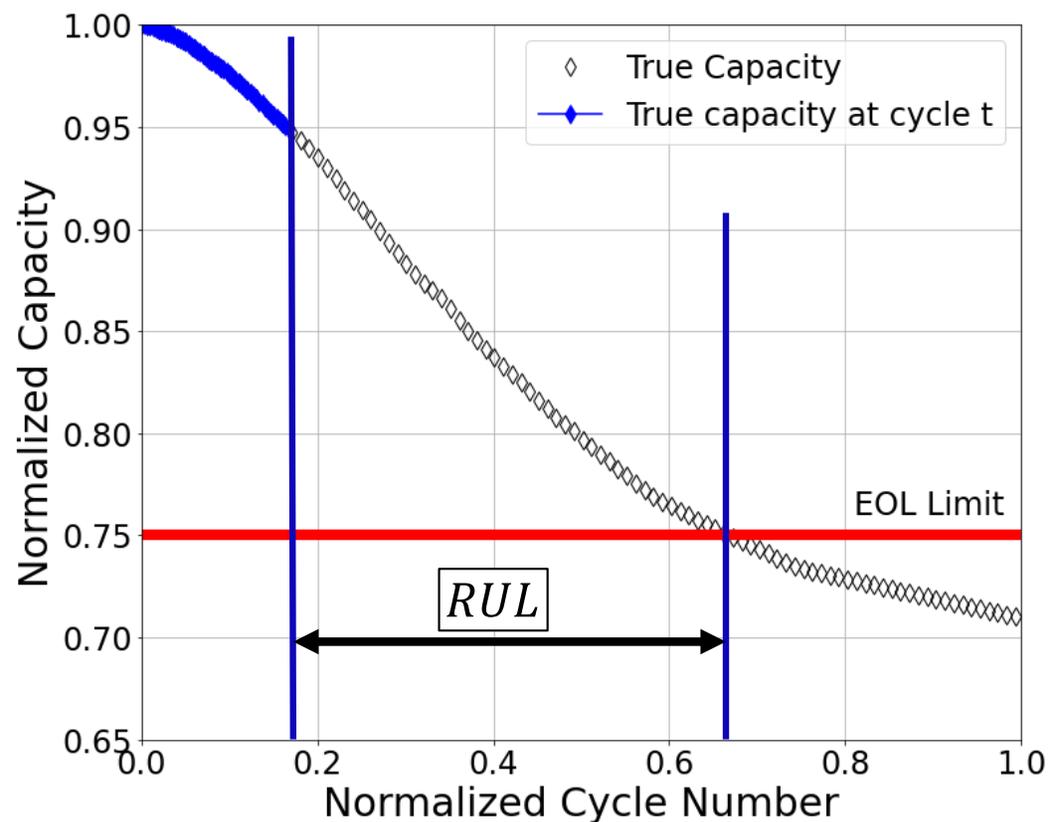
Capacity Fade of Hybrid Energy Storage Devices in Cycle Ageing Study



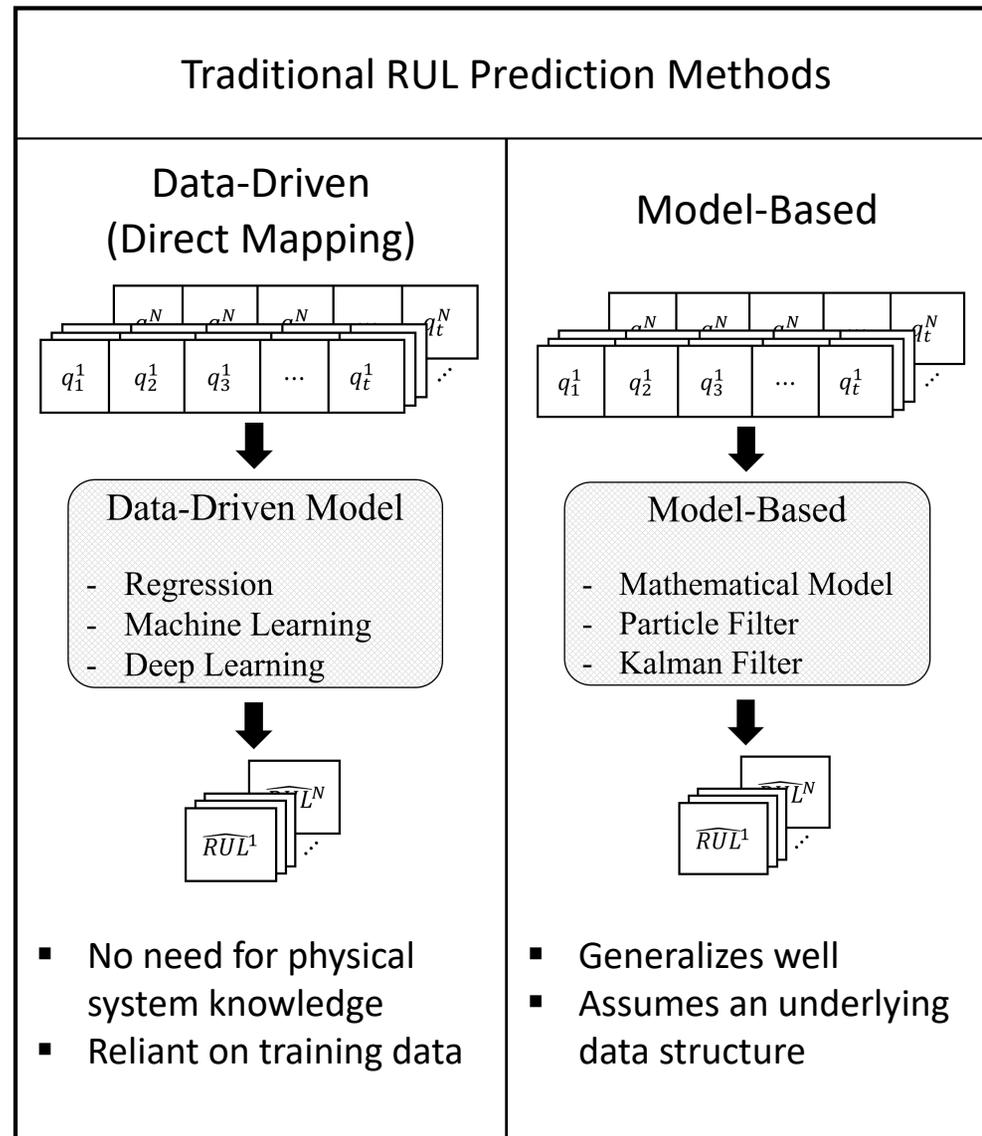
- All the ten hybrid energy storage devices (cells) were charged/discharged under C/5.
- The capacity fade trend of each cell is nonlinear and time-varying.

Remaining Useful Life Definition

- Remaining Useful Life (RUL) is subjectively defined as the number of remaining cycles a battery cell can undergo before reaching 75% of its initial capacity (i.e., the end-of-life (EOL) limit).

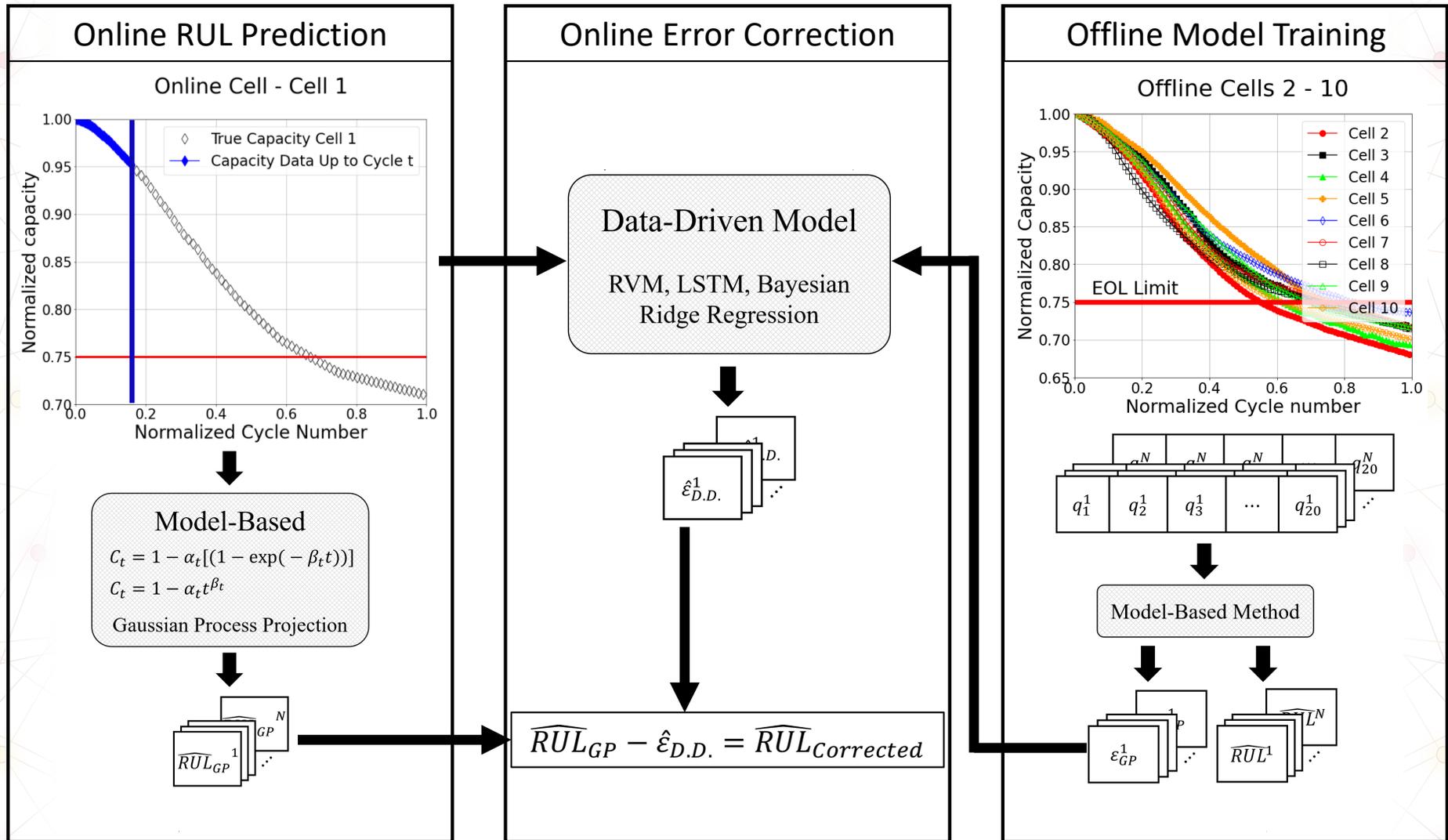


Model-Based and Data-Driven RUL Prediction Methods

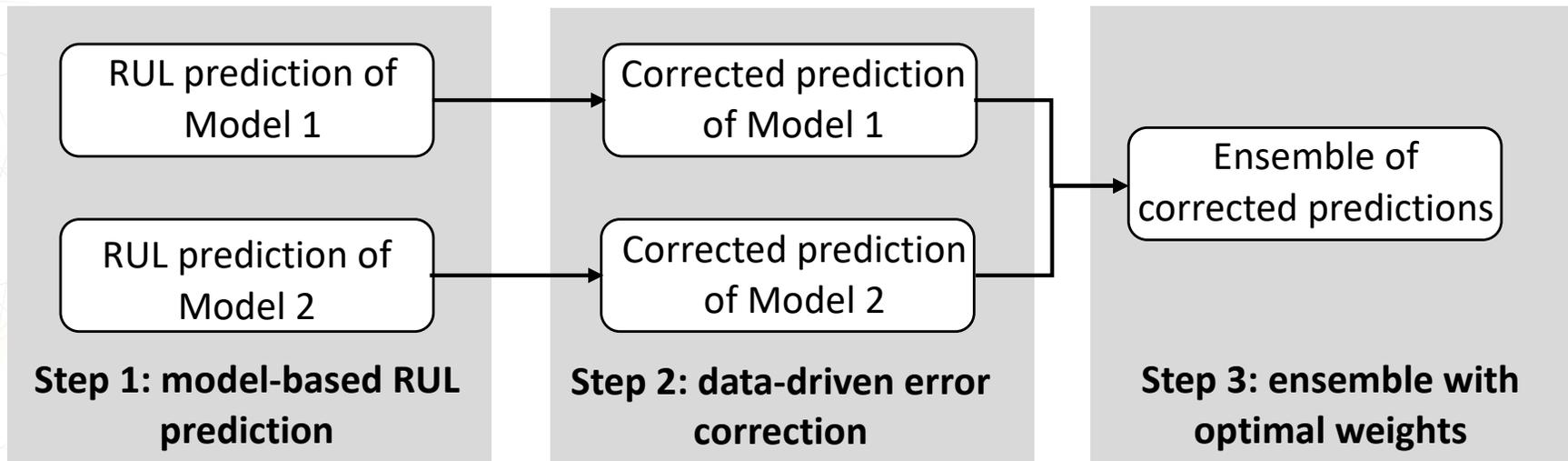


Model-Based/Data-Driven RUL Prediction Method

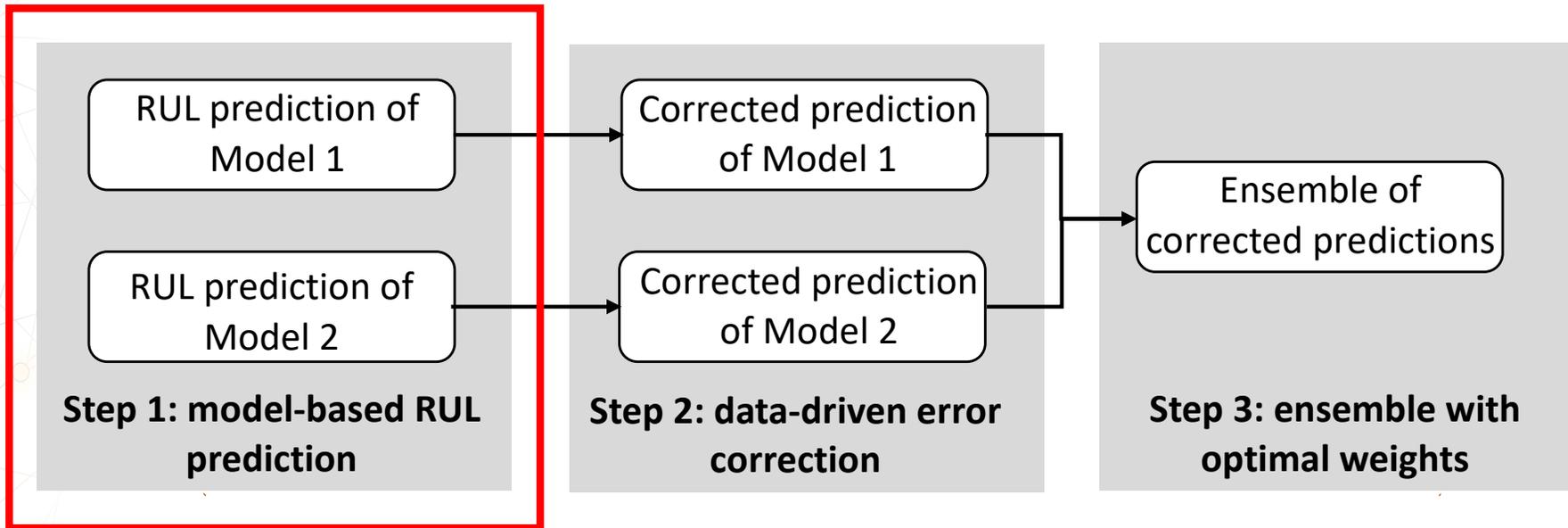
Model-Based Projection with Data-Driven Error Correction



Flowchart of Integrated Model-Based/Data-Driven RUL Prediction Framework



Flowchart of Integrated Model-Based/Data-Driven RUL Prediction Framework



Model-Based RUL Prediction with Gaussian Process

Gaussian Process (Kriging)

$$C(t) = \underbrace{M(t)}_{\text{trend function}} + \underbrace{Z(t)}_{N(0, \sigma^2)}$$

Trend Function $M(t)$

Model 1: $C_t = 1 - \alpha_t [(1 - \exp(-\beta_t t))]$

Model 2: $C_t = 1 - \alpha_t t^{\beta_t}$

where t is the cycle number, α_t and β_t are the coefficients to be curve fit using all the online cell data up to cycle t .

- A Gaussian process (GP) defines a probability distribution over a function, in our case, the trend functions $M(t)$. It is denoted as

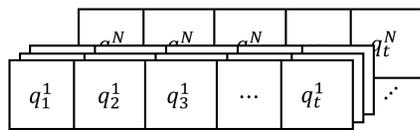
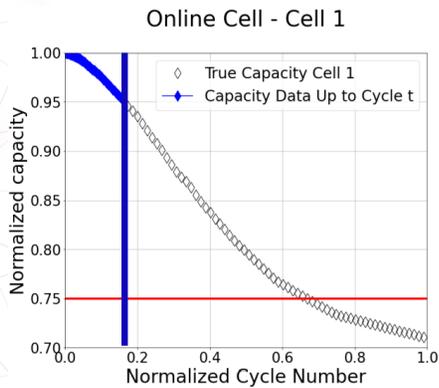
$$f(t) \sim GP(m(t), k(t, t'))$$

where $m(t)$ and $k(t, t')$ are the trend function and covariance function of the GP model

$$m(t) = E[f(t)]$$

$$k(t, t') = E[(f(t) - m(t))(f(t') - m(t'))^T]$$

Model-Based RUL Prediction with Gaussian Process

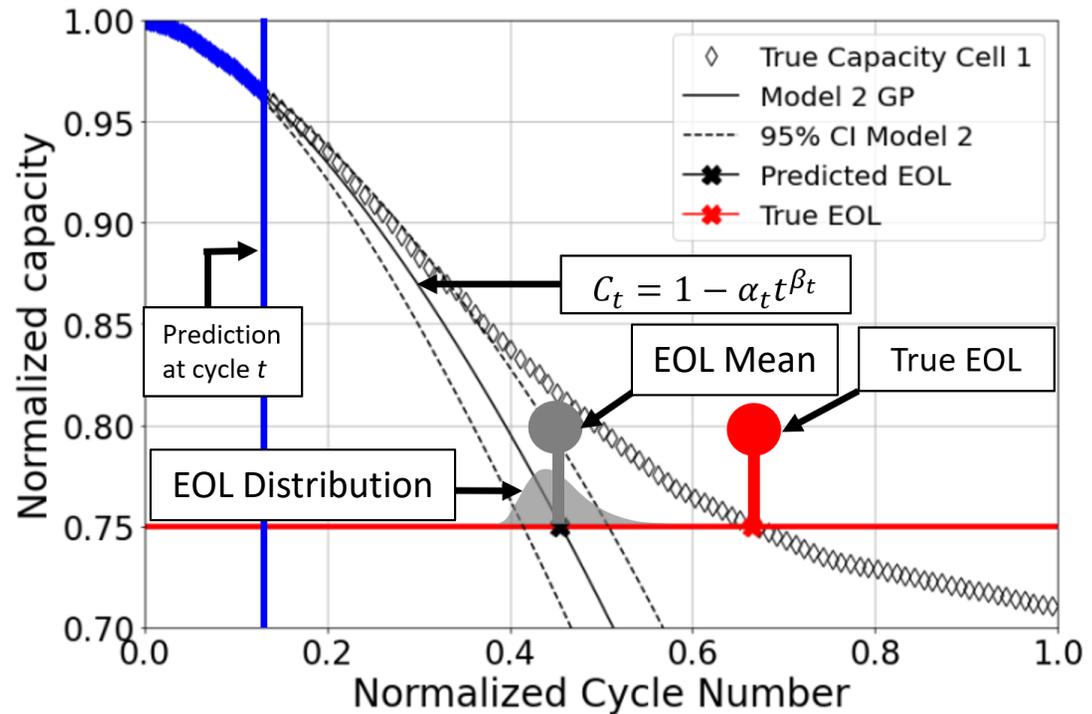
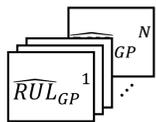


Model-Based

$$C_t = 1 - \alpha_t [(1 - \exp(-\beta_t t))]$$

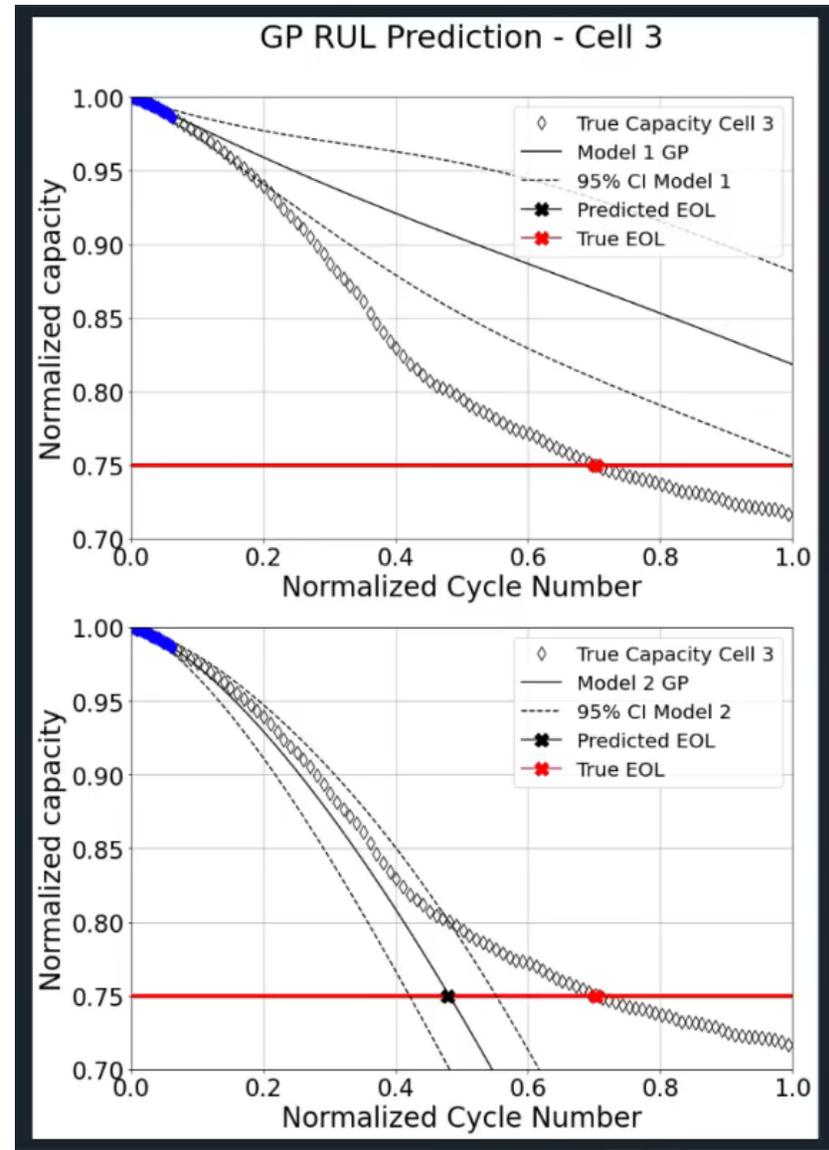
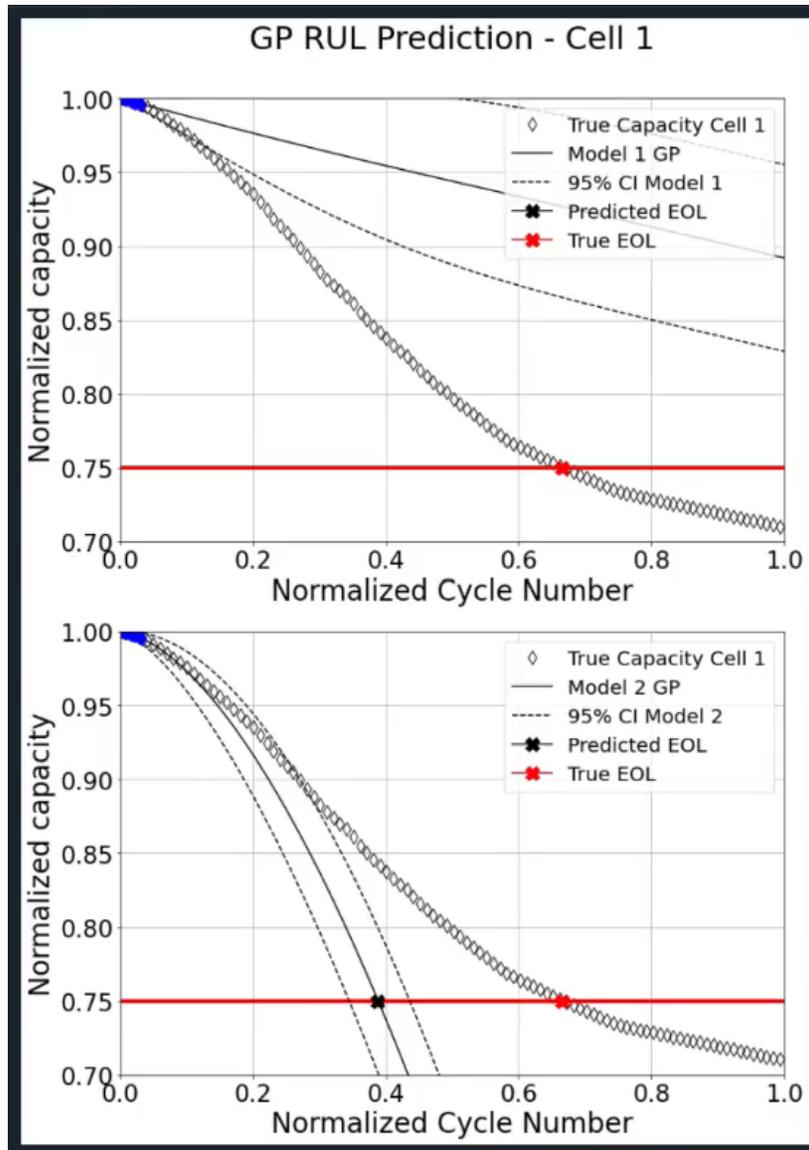
$$C_t = 1 - \alpha_t t^{\beta_t}$$

Gaussian Process Projection

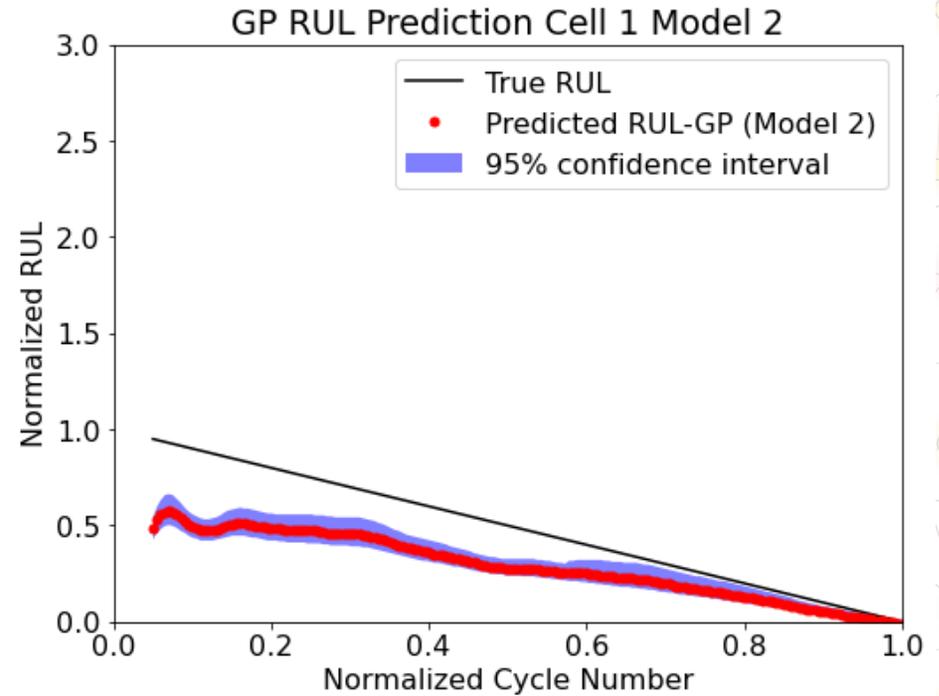
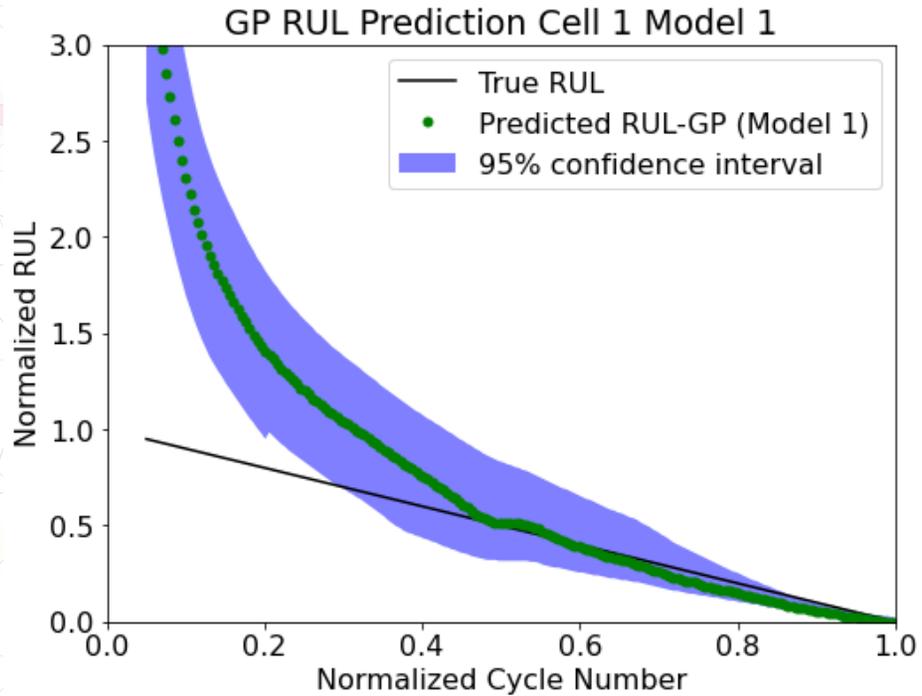


Example figure showing the probabilistic Gaussian Process projection using the underlying function $C_t = 1 - \alpha_t t^{\beta_t}$ (Model 2)

Model-Based RUL Prediction with Gaussian Process

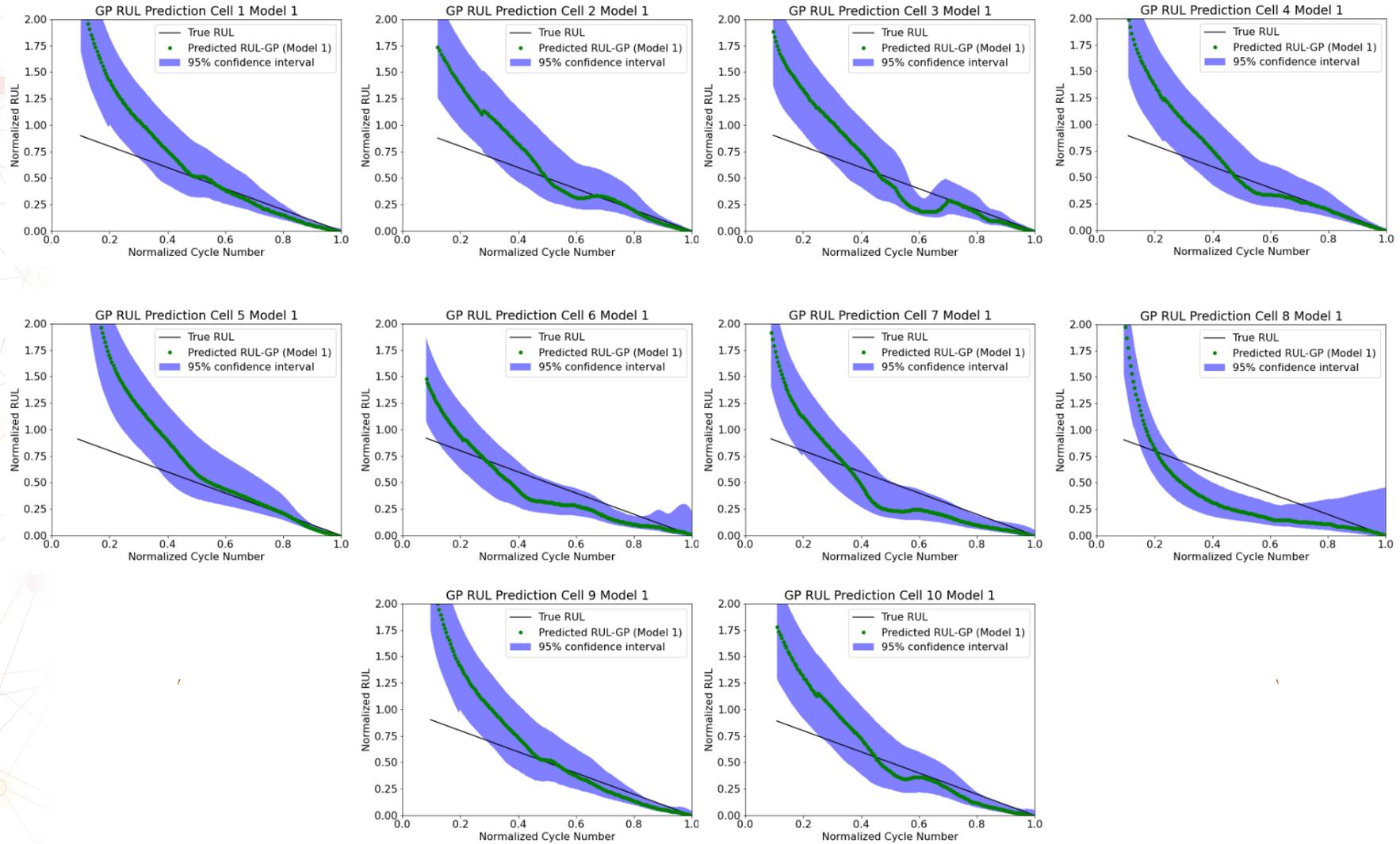


Model-Based RUL Prediction with Gaussian Process

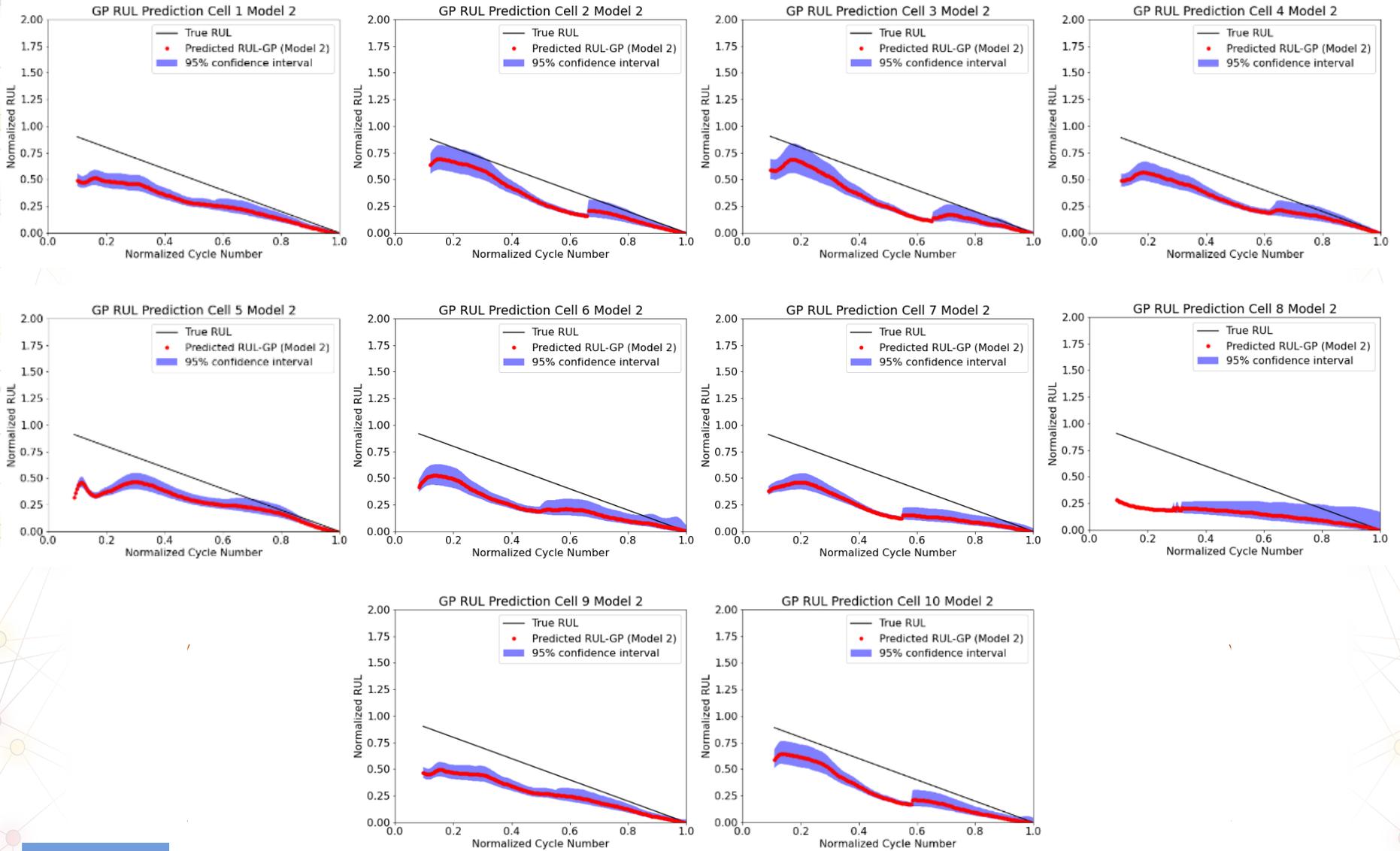


RUL prediction results with GP using Model 1 (left) and Model 2 (right) as the trend functions on Cell 1

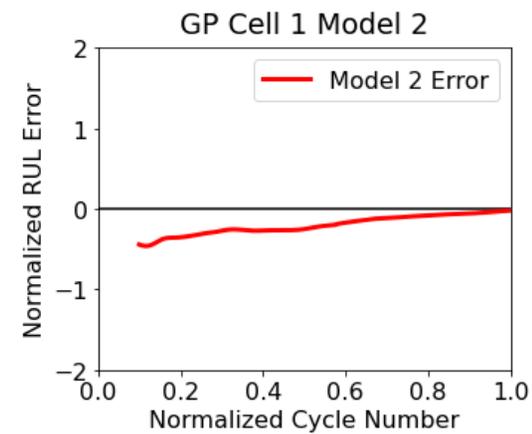
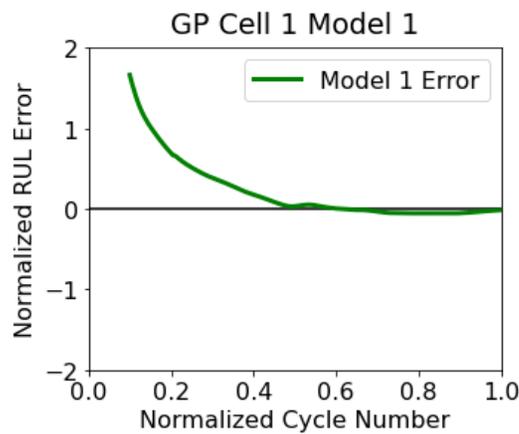
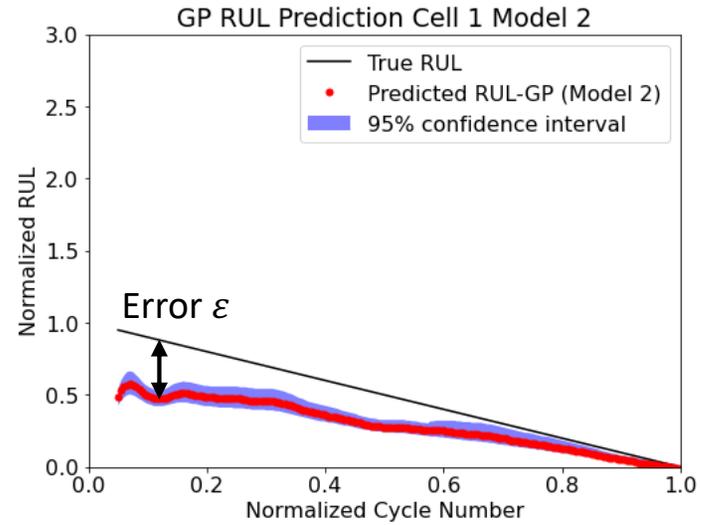
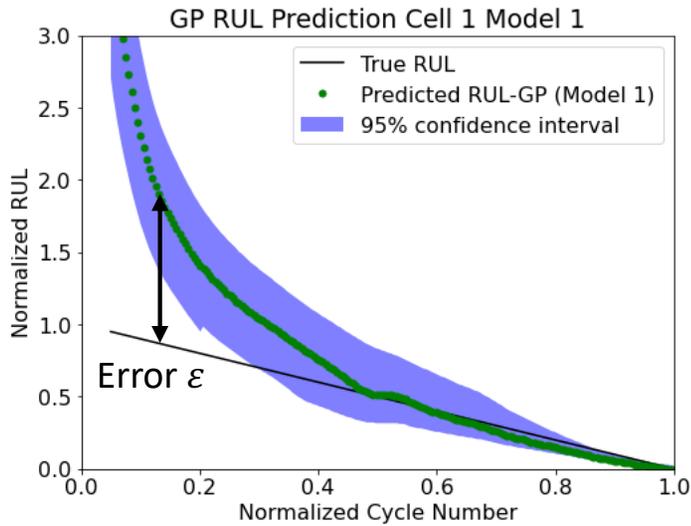
Model-Based RUL Prediction with Gaussian Process – Model 1



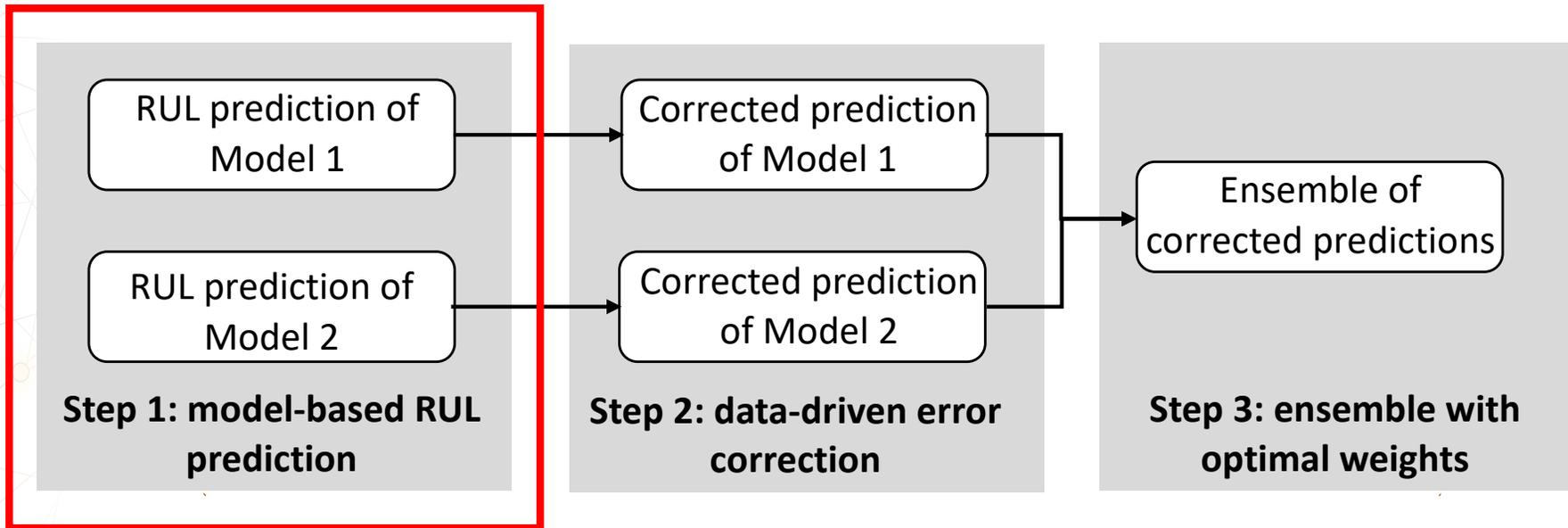
Model-Based RUL Prediction with Gaussian Process – Model 2



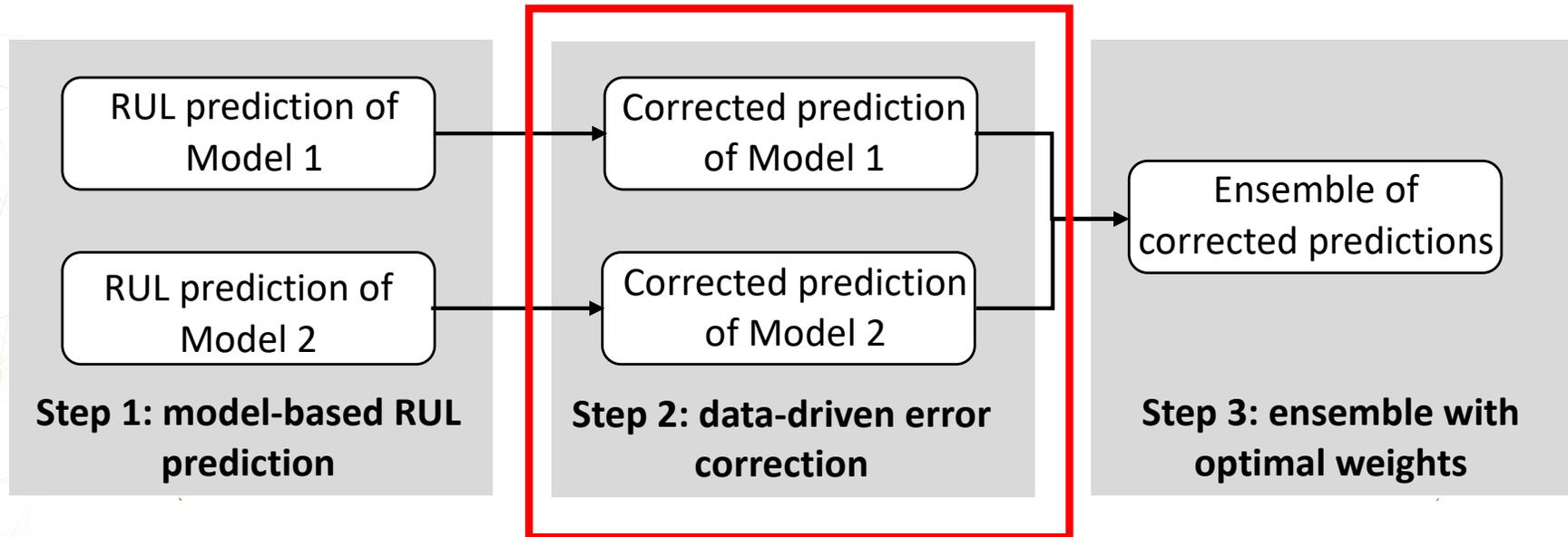
Model-Based RUL Prediction with Gaussian Process – Error



Flowchart of Integrated Model-Based/Data-Driven RUL Prediction Framework



Flowchart of Integrated Model-Based/Data-Driven RUL Prediction Framework

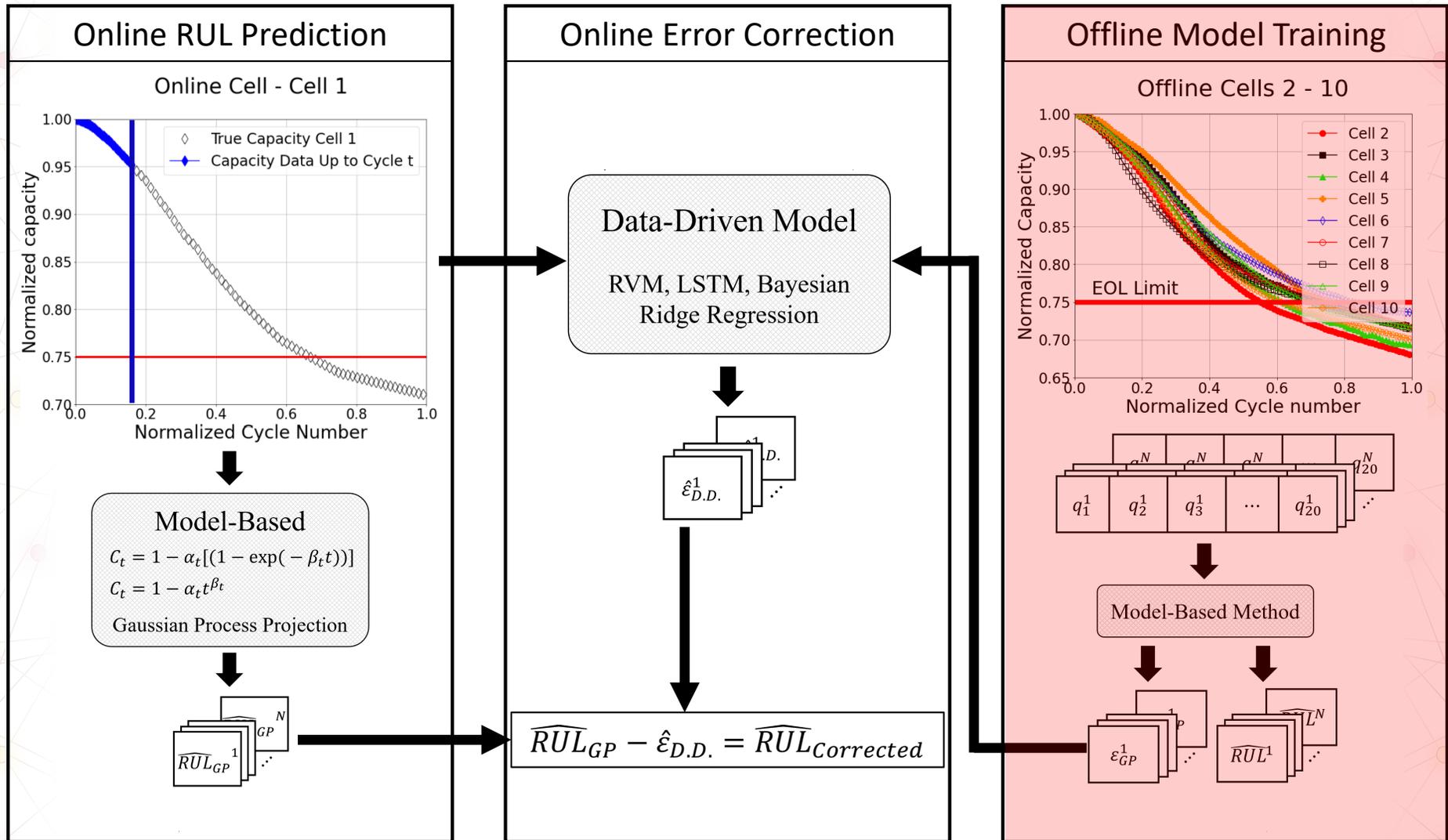


Notes

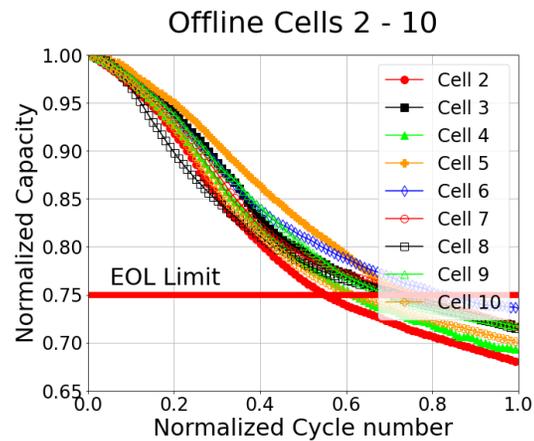
- Offline data includes the capacity measurements and the true RULs of the offline cells.
 - The data-driven method is trained using the offline data.
- Online data includes the capacity measurements of an online cell up to the current cycle.

Model-Based/Data-Driven RUL Prediction Method

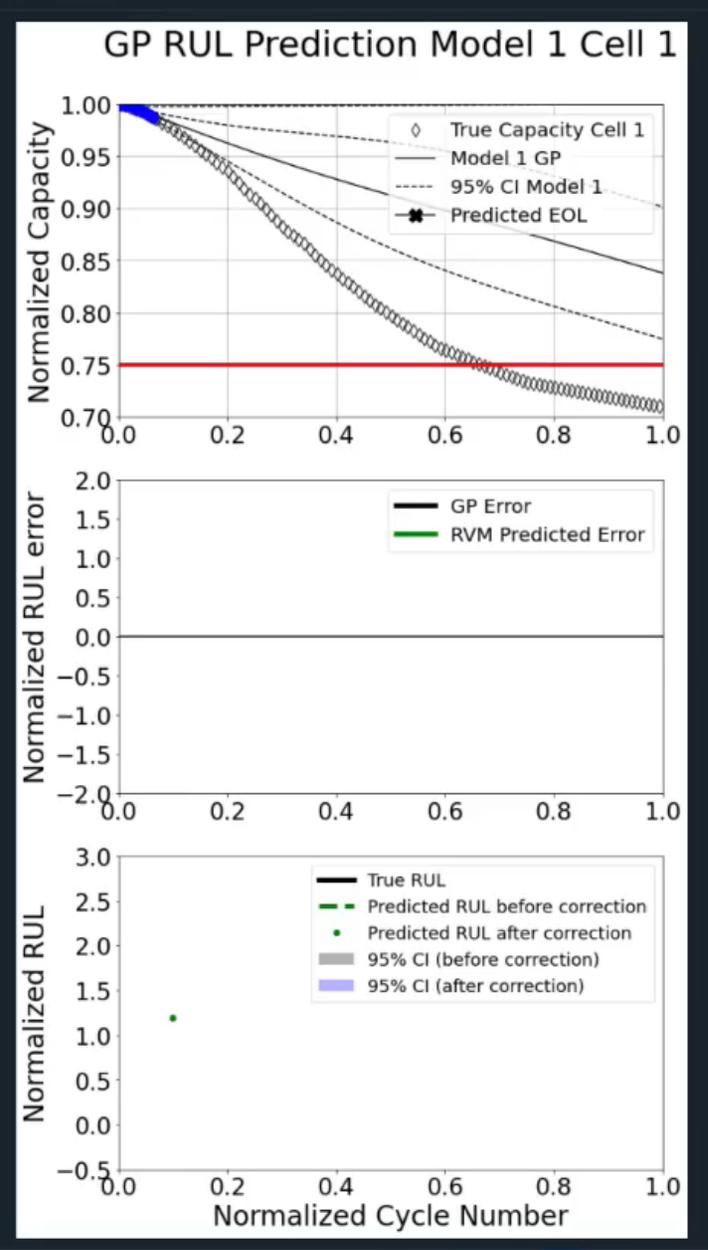
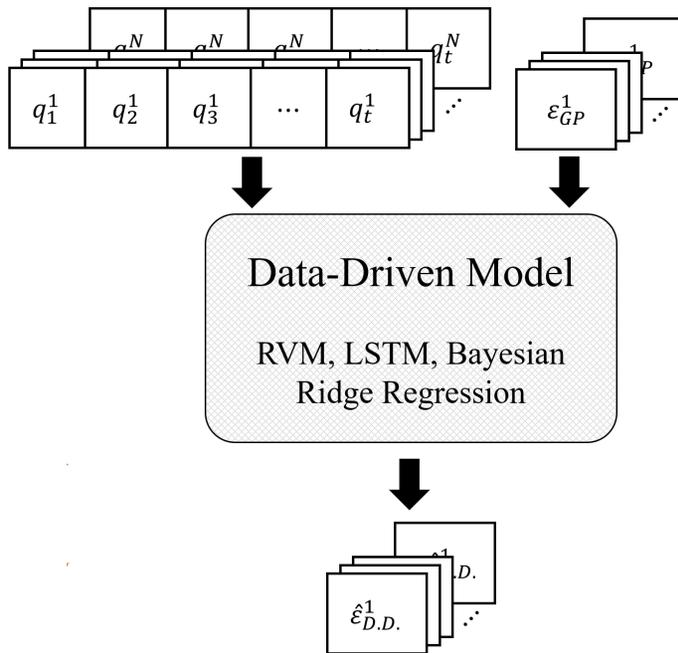
Model-Based Projection with Data-Driven Error Correction



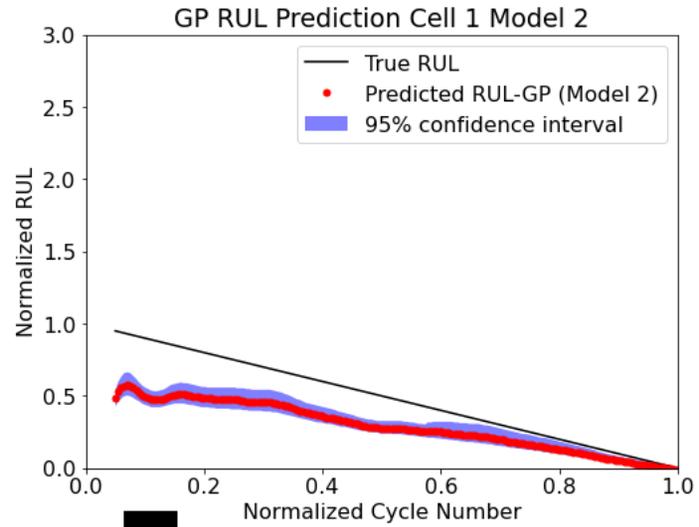
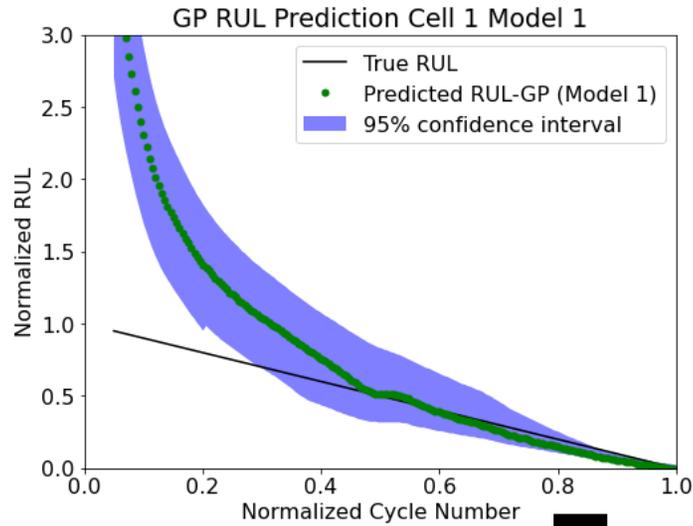
Data-Driven Model – Error Prediction Results



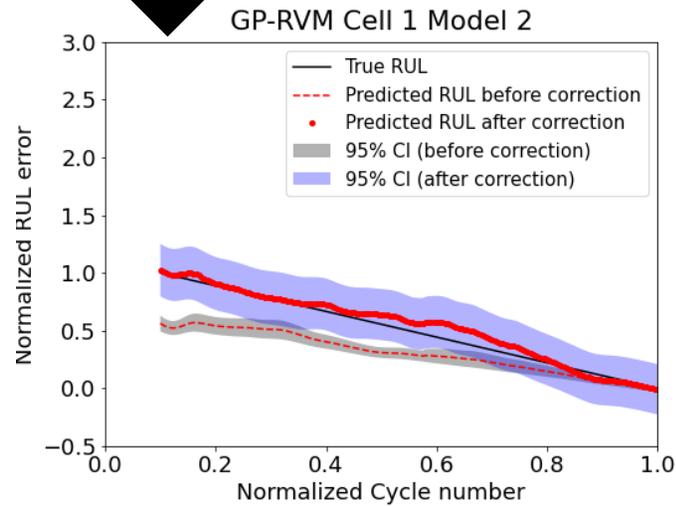
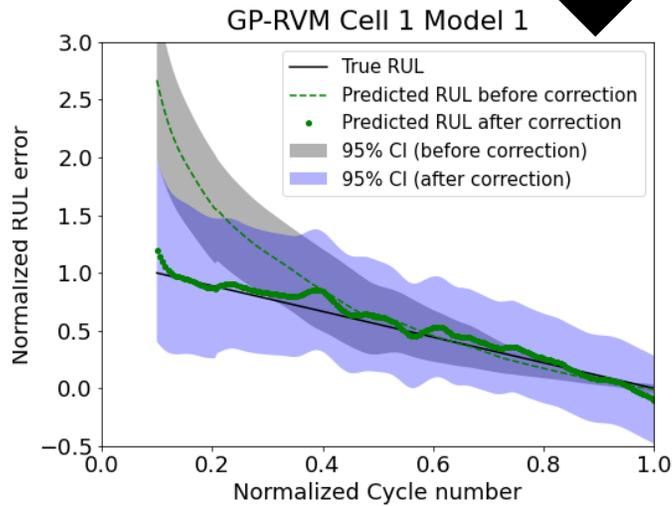
Offline Data-Driven Model Training



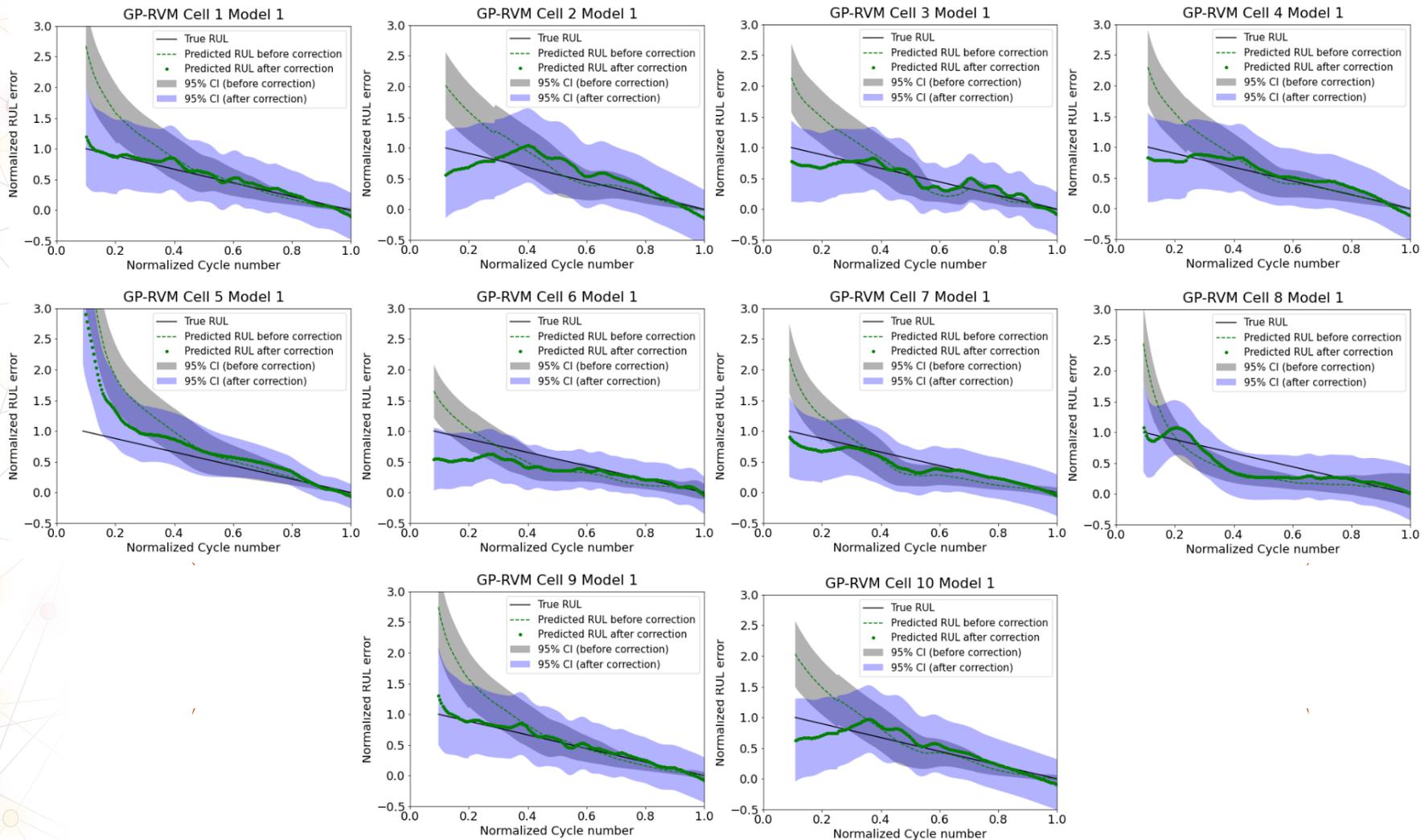
Data-Driven Error Correction Results



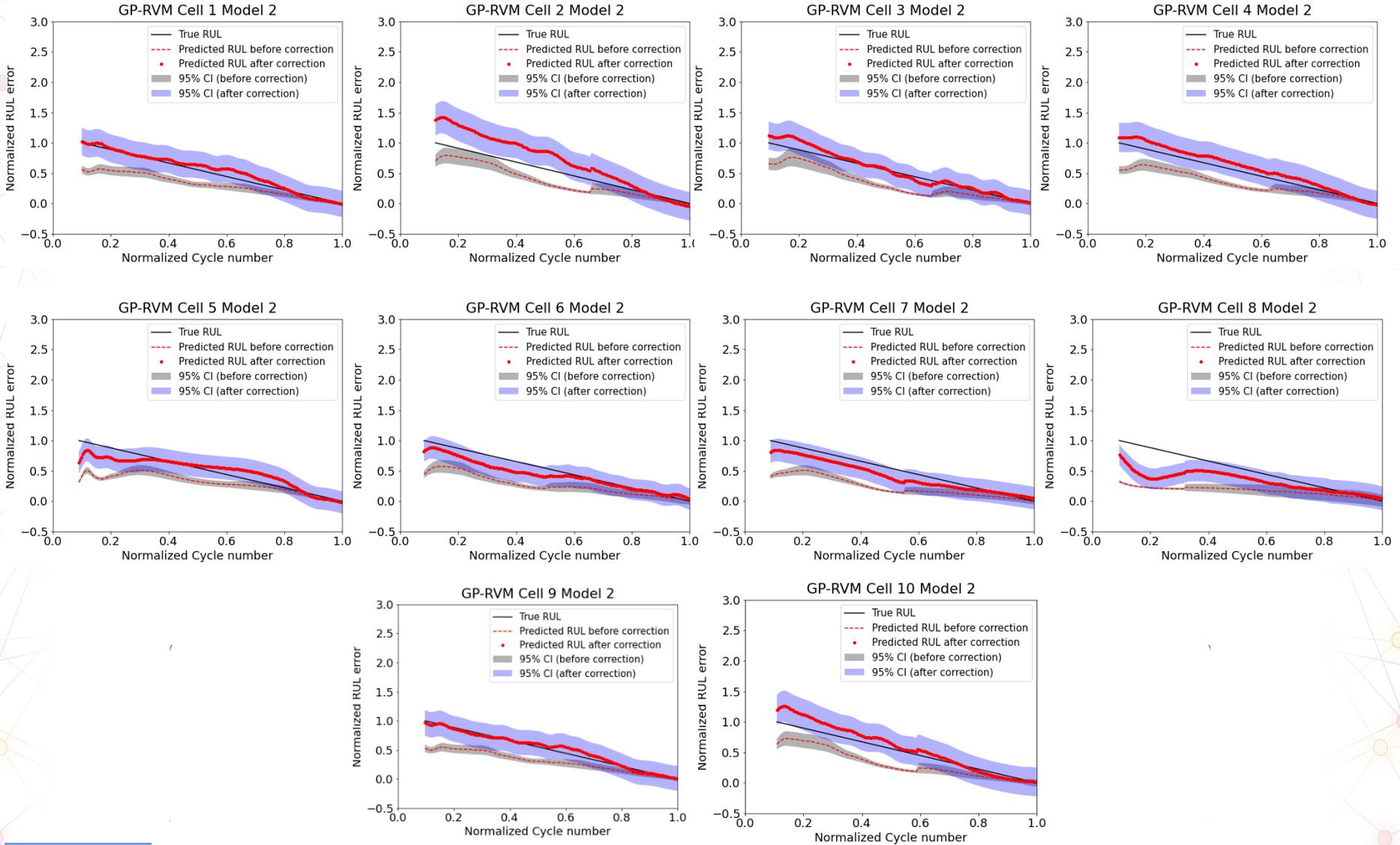
$$\widehat{RUL}_{GP} - \hat{\epsilon}_{D.D.} = \widehat{RUL}_{Corrected}$$



Data-Driven Error Correction Results – Model 1



Data-Driven Error Correction Results – Model 2



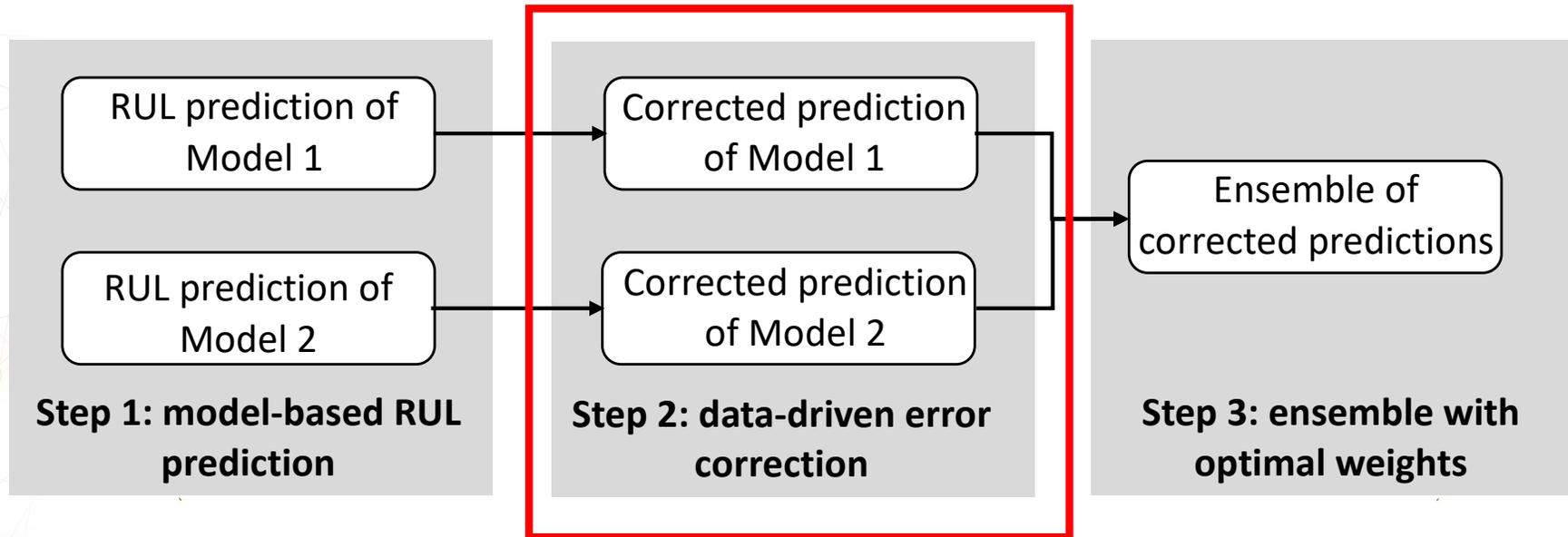
Results for Different Data-Driven Error Correction Methods

- Data-driven error correction improves the overall prediction accuracy
 - Compared to purely model-based projection (GP)

	Method	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6	Cell 7	Cell 8	Cell 9	Cell 10	Average
		RMSE	RMSE									
Model 1	GP	77.7	49.8	65.5	59.8	161.3	39.9	59.3	59.3	81.3	52.3	70.6
	GP-LSTM-RMSE	22.9	47.5	20.9	32.4	105.9	42.5	24.8	48.4	36.6	28.1	41.0
	GP-LSTM-KL	42.8	31.3	35.1	18.8	131.0	26.6	27.9	48.4	47.7	15.9	42.6
	GP-LSTM-NLL	36.2	24.1	23.6	18.0	132.1	41.2	26.7	44.3	42.0	16.4	40.5
	GP-RVM	11.8	28.4	22.3	17.4	90.8	44.4	22.2	32.3	11.3	23.0	30.4
	GP-Ridge Regression	22.7	45.1	16.4	23.5	101.7	52.5	28.8	37.1	23.3	26.4	37.7
Model 2	GP	40.8	23.3	38.8	35.3	52.8	62.6	63.7	78.4	44.9	34.7	47.5
	GP-LSTM-RMSE	15.2	34.9	20.8	17.2	19.3	21.5	21.8	35.8	10.1	17.9	21.5
	GP-LSTM-KL	21.7	54.3	37.1	36.4	18.3	21.4	24.6	36.5	28.4	38.1	31.7
	GP-LSTM-NLL	15.7	33.9	20.5	18.7	24.1	19.8	22.8	37.5	9.2	17.3	21.9
	GP-RVM	11.2	35.6	14.4	16.3	22.6	23.4	21.9	45.2	8.8	19.8	21.9
	GP-Ridge Regression	11.9	33.5	18.9	17.9	20.1	23.4	23.6	40.6	8.8	19.1	21.8

Color-coded by Cell

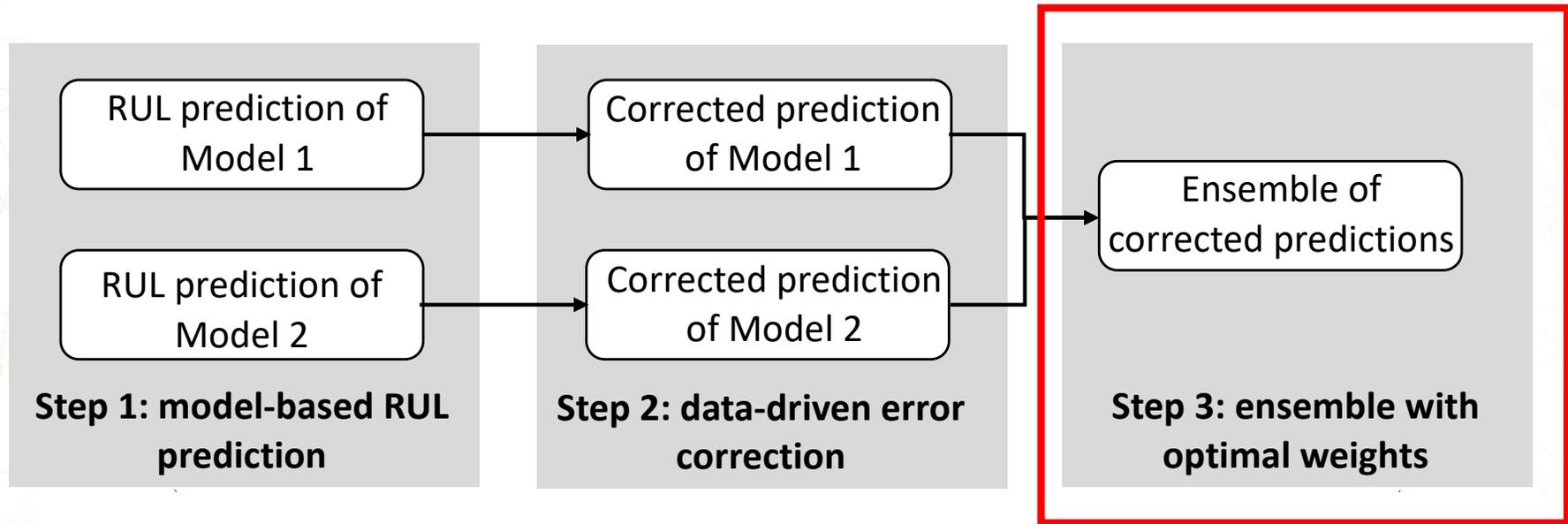
Flowchart of Integrated Model-Based/Data-Driven RUL Prediction Framework



Notes

- Online data includes the capacity measurements of an online cell up to the current cycle.
- Offline data includes the capacity measurements and the true RULs of the offline cells.
 - The data-driven method is trained using the offline data

Flowchart of Integrated Model-Based/Data-Driven RUL Prediction Framework



Notes

- Online data includes the capacity measurements of an online cell up to the current cycle.
- Offline data includes the capacity measurements and the true RULs of the offline cells.
 - The data-driven method is trained using the offline data

Data-Driven Error Correction Ensemble Methods

Weighted Average Method

$$\text{Model 1: } x \sim N(\mu_x, \sigma_x^2)$$

$$\text{Model 2: } y \sim N(\mu_y, \sigma_y^2)$$

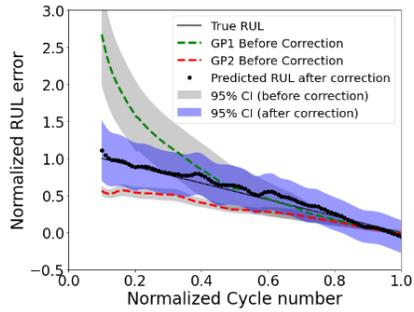
$$\begin{aligned} \text{Corrected Average} &\triangleq \alpha x + (1 - \alpha)y \\ &= N(\alpha\mu_x + (1 - \alpha)\mu_y, \alpha^2\sigma_x^2 + (1 - \alpha)^2\sigma_y^2) \end{aligned}$$

$$\text{Equal Weight Average: } \alpha = 0.5$$

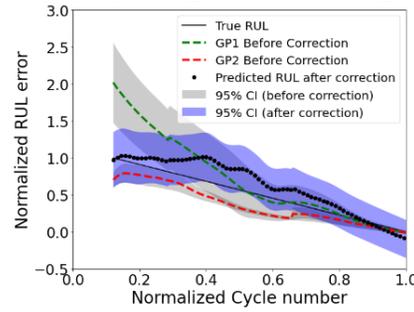
Note: Also investigating optimization-based weighting methods

Equal Weight Average of Data-Driven Error Correction – Results

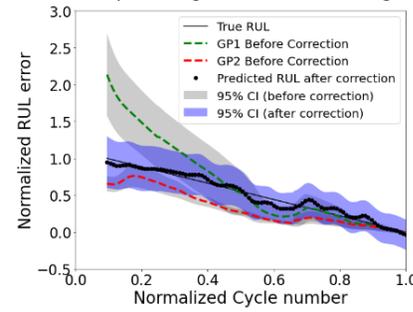
GP-RVM Equal Weight Corrected Average Cell 1



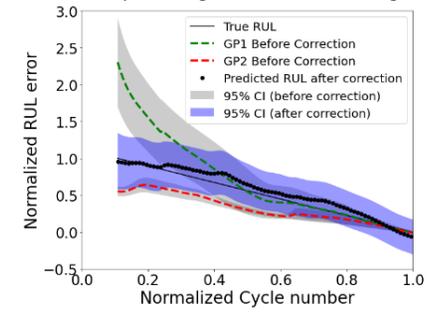
GP-RVM Equal Weight Corrected Average Cell 2



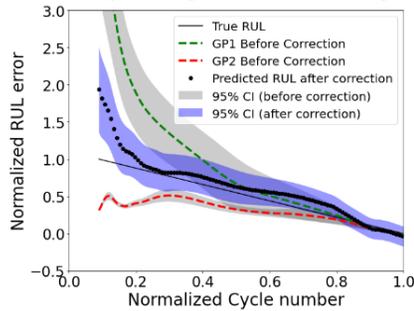
GP-RVM Equal Weight Corrected Average Cell 3



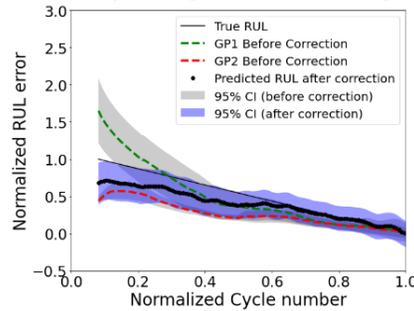
GP-RVM Equal Weight Corrected Average Cell 4



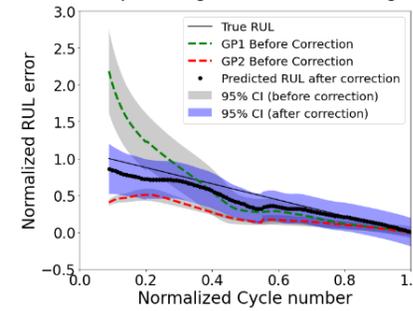
GP-RVM Equal Weight Corrected Average Cell 5



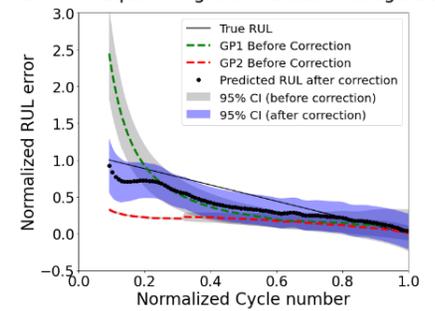
GP-RVM Equal Weight Corrected Average Cell 6



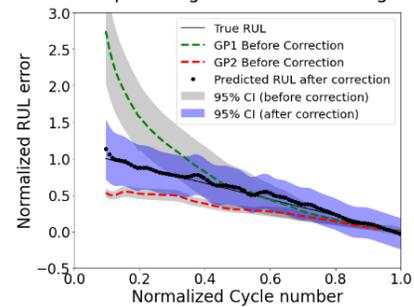
GP-RVM Equal Weight Corrected Average Cell 7



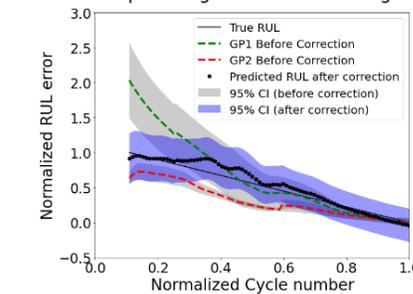
GP-RVM Equal Weight Corrected Average Cell 8



GP-RVM Equal Weight Corrected Average Cell 9



GP-RVM Equal Weight Corrected Average Cell 10



Data-Driven Direct Mapping and Corrected Average Comparison

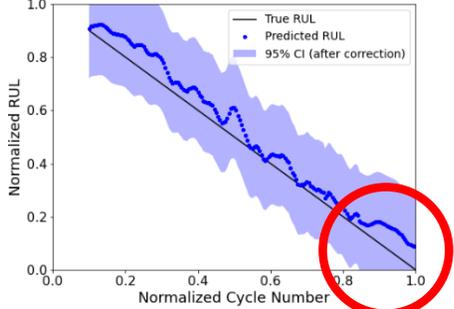
- The ensemble further improves the accuracy of the error correction.
 - This could be further improved with more models, or weight optimization

Method	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6	Cell 7	Cell 8	Cell 9	Cell 10	Average
	RMSE	RMSE									
Direct Map-LSTM	16.3	52.6	9.5	9.8	19.4	33.0	26.6	13.3	9.7	22.6	21.3
Direct Map-RVM	11.8	28.6	6.8	16.6	13.3	28.1	20.7	30.4	7.9	13.8	17.8
Direct Map-BRR	11.8	31.7	8.2	18.4	7.9	31.7	21.3	23.8	8.0	16.5	17.9
Model 1 GP-RVM	11.8	28.4	22.3	17.4	90.8	44.4	22.2	32.3	11.3	23.0	30.4
Model 2 GP-RVM	11.2	35.6	14.4	16.3	22.6	23.4	21.9	45.2	8.8	19.8	21.9
GP-RVM Ensemble	10.5	25.4	10.7	13.9	40.7	32.8	21.2	30.3	7.8	13.8	20.7

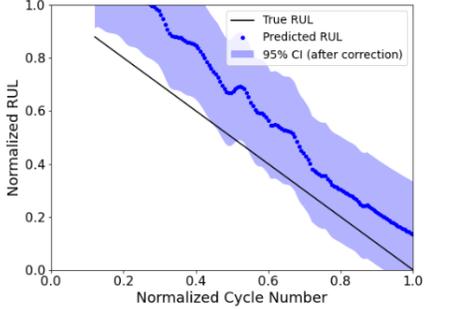
Color-coded by Cell

Data-Driven Direct Mapping and Corrected Average Comparison

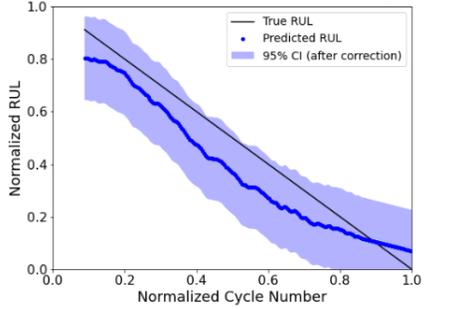
Bayesian Ridge Regression Direct Mapping Cell 1



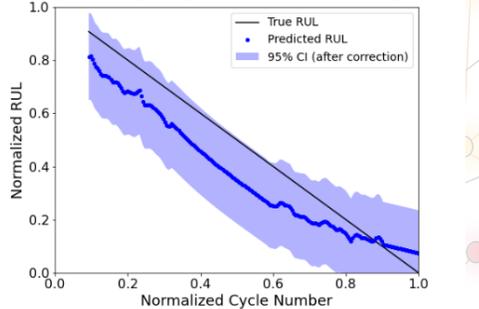
Bayesian Ridge Regression Direct Mapping Cell 2



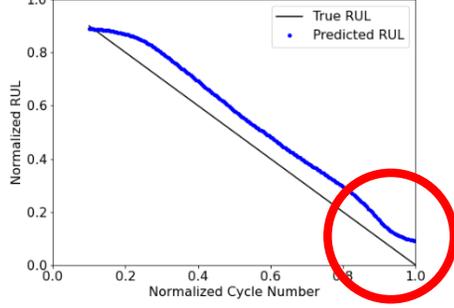
Bayesian Ridge Regression Direct Mapping Cell 7



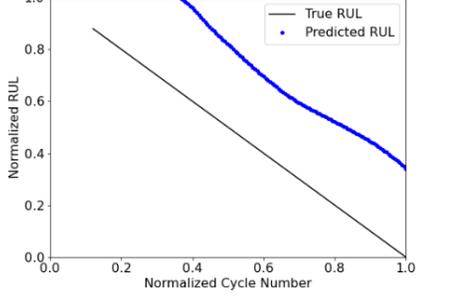
Bayesian Ridge Regression Direct Mapping Cell 8



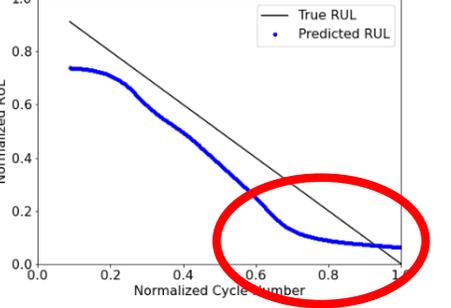
LSTM RMSE Direct Mapping Cell 1



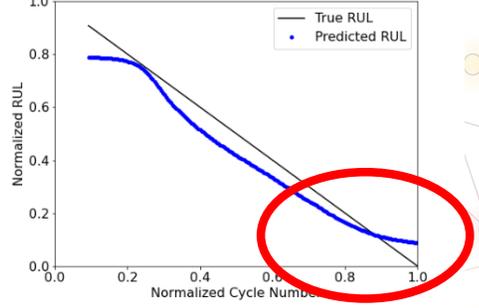
LSTM RMSE Direct Mapping Cell 2



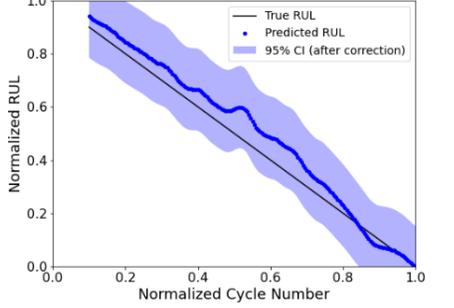
LSTM RMSE Direct Mapping Cell 7



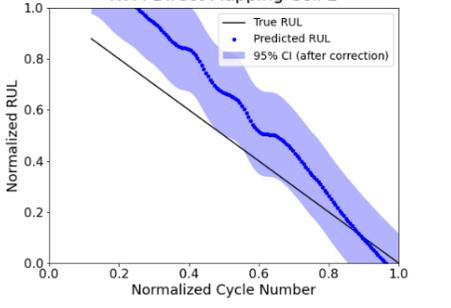
LSTM RMSE Direct Mapping Cell 8



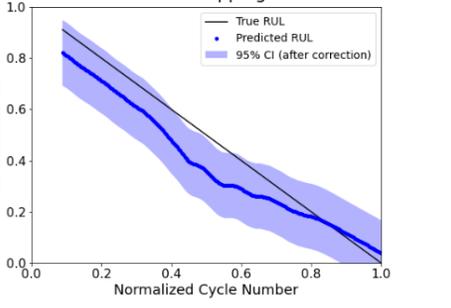
RVM Direct Mapping Cell 1



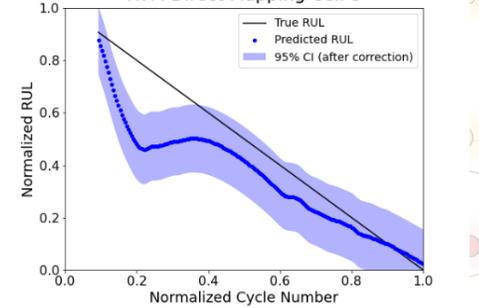
RVM Direct Mapping Cell 2



RVM Direct Mapping Cell 7



RVM Direct Mapping Cell 8



Cell 1

Cell 2

Cell 7

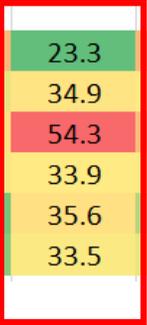
Cell 8



Data-Driven Direct Mapping and Corrected Average Comparison

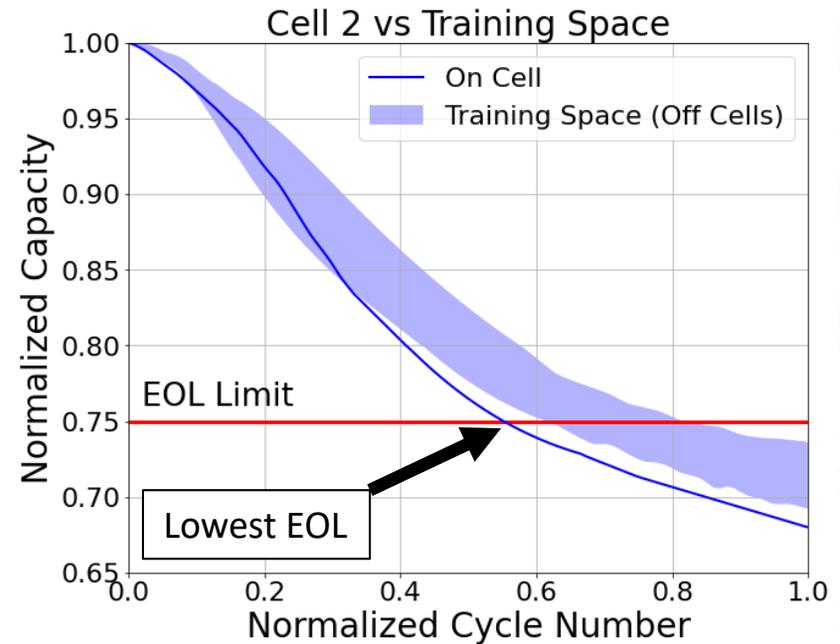
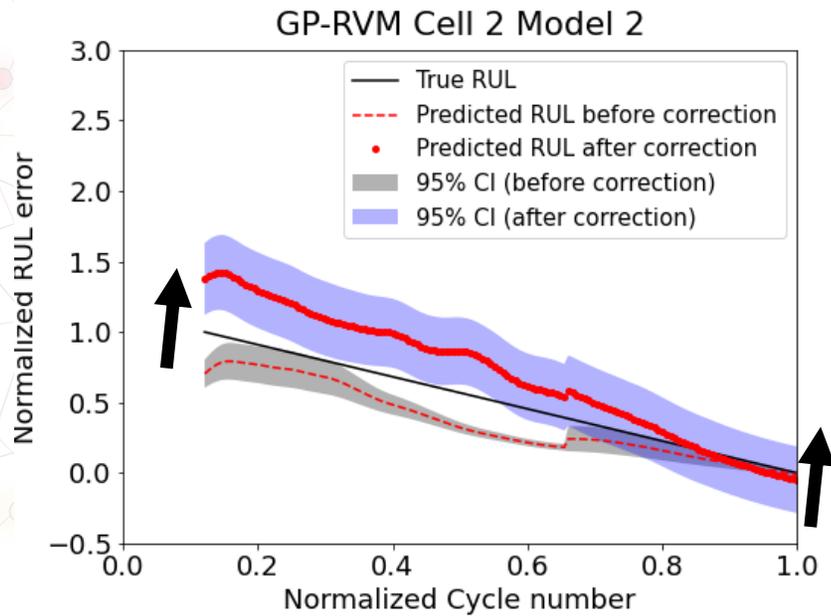
- Cell 2 RUL prediction performance is poor across the board. . .why?

	Method	Cell 1	Cell 2	Cell 3	Cell 4	Cell 5	Cell 6	Cell 7	Cell 8	Cell 9	Cell 10	Average
		RMSE	RMSE									
Model 1	GP	77.7	49.8	65.5	59.8	161.3	39.9	59.3	59.3	81.3	52.3	70.6
	GP-LSTM-RMSE	22.9	47.5	20.9	32.4	105.9	42.5	24.8	48.4	36.6	28.1	41.0
	GP-LSTM-KL	42.8	31.3	35.1	18.8	131.0	26.6	27.9	48.4	47.7	15.9	42.6
	GP-LSTM-NLL	36.2	24.1	23.6	18.0	132.1	41.2	26.7	44.3	42.0	16.4	40.5
	GP-RVM	11.8	28.4	22.3	17.4	90.8	44.4	22.2	32.3	11.3	23.0	30.4
	GP-Ridge Regression	22.7	45.1	16.4	23.5	101.7	52.5	28.8	37.1	23.3	26.4	37.7
Model 2	GP	40.8	23.3	38.8	35.3	52.8	62.6	63.7	78.4	44.9	34.7	47.5
	GP-LSTM-RMSE	15.2	34.9	20.8	17.2	19.3	21.5	21.8	35.8	10.1	17.9	21.5
	GP-LSTM-KL	21.7	54.3	37.1	36.4	18.3	21.4	24.6	36.5	28.4	38.1	31.7
	GP-LSTM-NLL	15.7	33.9	20.5	18.7	24.1	19.8	22.8	37.5	9.2	17.3	21.9
	GP-RVM	11.2	35.6	14.4	16.3	22.6	23.4	21.9	45.2	8.8	19.8	21.9
	GP-Ridge Regression	11.9	33.5	18.9	17.9	20.1	23.4	23.6	40.6	8.8	19.1	21.8



Color-coded by Cell

Training Data Investigation: Model 2 Cell 2



Model 2	GP	40.8	23.3
GP-LSTM-RMSE	15.2	34.9	
GP-LSTM-KL	21.7	54.3	
GP-LSTM-NLL	15.7	33.9	
GP-RVM	11.2	35.6	
GP-Ridge Regression	11.9	33.5	

- Model 2 Cell 2 RUL prediction is accurate because Model 2 consistently underestimates the EOL.
- The data-driven error correction models train on cells with higher EOL, which causes over-correction.

Conclusions and Future Work

Conclusions

- Using both model-based and data-driven methods allows us to dynamically adjust between the two in the final output.
 - Useful when we know one method will perform better in a certain setting. i.e. end of life convergence.
- An ensemble of models provides increased accuracy.

Future Work

- Develop an algorithm to weigh the error correction based on data-driven model confidence.
 - Examine methods to detect outliers in a dataset (e.g. Cell 2) and quantify their levels of deviation.

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