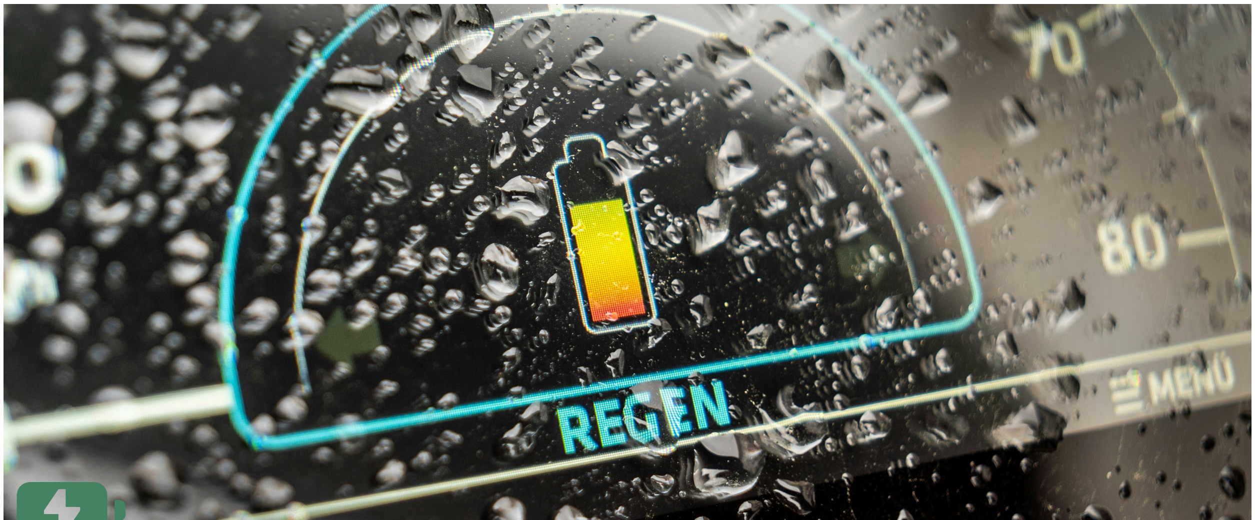

SPT Proposal

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This report can also be viewed online for a better experience.

SPT Proposal

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Challenge Identification

In these challenges, we are trying to utilize AI clean energy systems, including outlining AI concepts, energy application modeling, usage logic, and expected outcomes. In short words:

> ❓ How can AI optimize the use and application of **battery storage technologies** in real-world energy challenges?

Among all the topics provided in the description (including but not limited to), I choose “EV Smarting Charging”.

At the SPT Introduction slides (Figure 1.1), “Combines solar power generation, energy storage systems, and electric vehicle charging functions” leads to future smart charging. Our task is to develop an AI feature, focusing on the battery storage bank at a charging station, and apply it to real-world challenges.

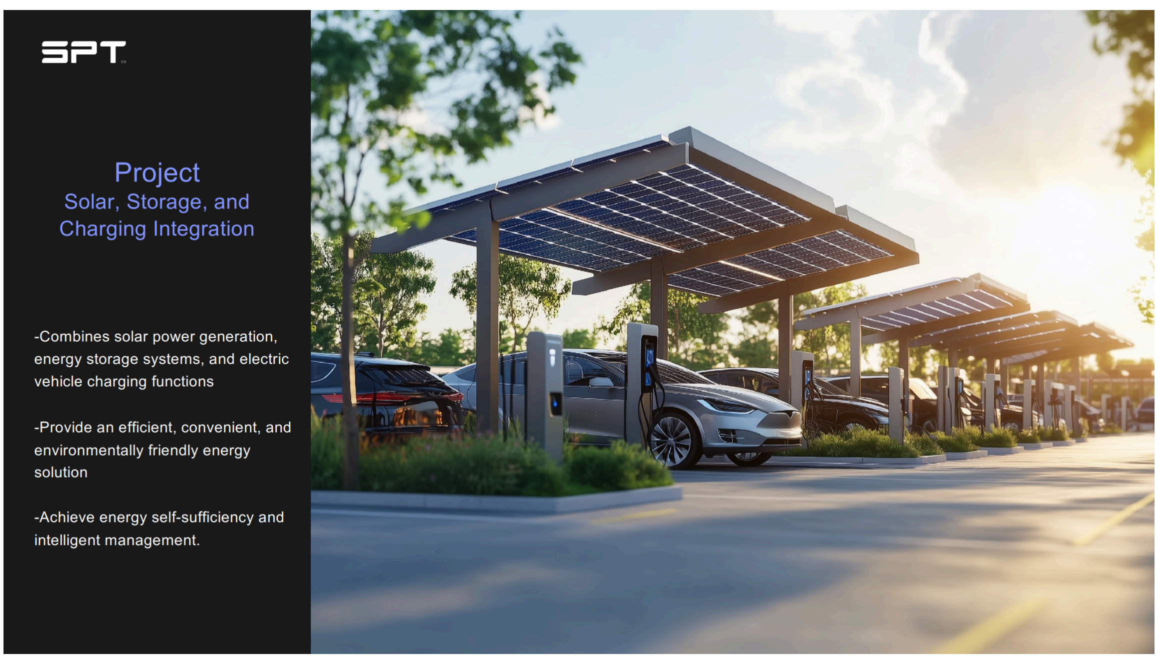

Figure 1.1 SPT Introduction slides for EV Charging

Let's jump directly into it.

Innovation Idea

There are many creative ideas I can think of, but I can't list all of them. Here I list five of the most creative/robust features across different dimensions: tackling fundamental challenges, leveraging market opportunities, enhancing reliability, and envisioning a more interconnected and optimized energy future.

For each feature, I also let AI generate a picture, so it's clearer and understandable.

Note: All outcomes and impacts are from research. Since those are just ideas, we don't know what the exact preference is. So I searched for some existing similar cases, and provided a number range.

Multi-Objective Optimizer

The Multi-Objective Optimizer uses AI to balance conflicting objectives in battery storage management, such as maximizing battery life, minimizing energy costs, and reducing carbon footprint.

Rather than optimizing for a single objective (e.g., cost), it finds the optimal balance between multiple objectives in real time. Models can dynamically adjust the charging and discharging strategies based on usage history, grid price, and battery temperature.

- **Model type:** multi-objective reinforcement learning or evolutionary algorithms
- **Riverside use case:** At SPT's battery-supported charging stations, this type of AI helps determine when to charge/discharge, how aggressively to run them, and how to balance operating costs with battery health, which is critical for reliability and sustainability.

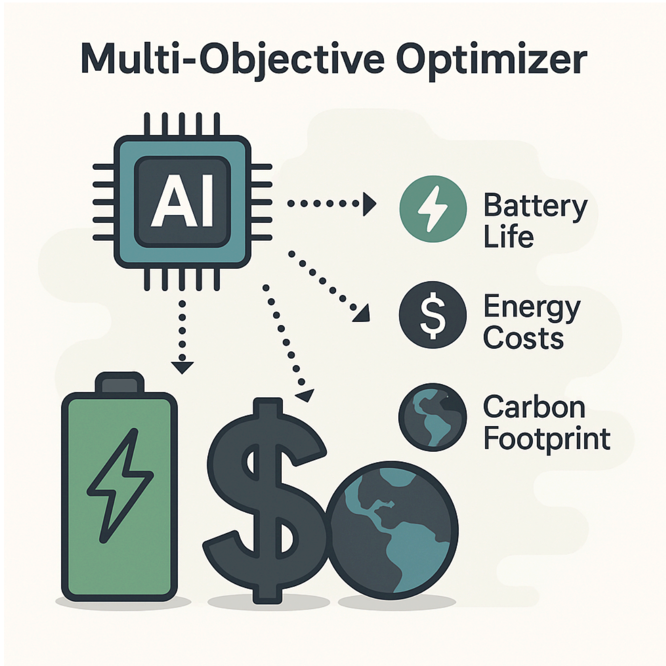

Figure 2.1 Multi-Objective Optimizer

Multi-objective optimization in energy systems can improve efficiency by **20–30%** and extend battery life by **10–20%**, depending on the use case and constraints.

Health-Aware Charging

Health-aware charging integrates AI technology to adjust the charge rate, depth, and duration based on the battery's current condition, temperature, and usage history. The goal is to minimize long-term battery performance degradation, avoid thermal stress, and extend battery life, rather than always aiming for the fastest possible charge rate.

- **Model type:** supervised learning or reinforcement learning using historical charging data
- **Riverside use case**: SPT's solar battery system can charge more aggressively when there is a surplus of solar energy, but when high temperatures or deep cycling accelerate wear and tear, especially during the hot Riverside summer months, the AI can slow down charging.

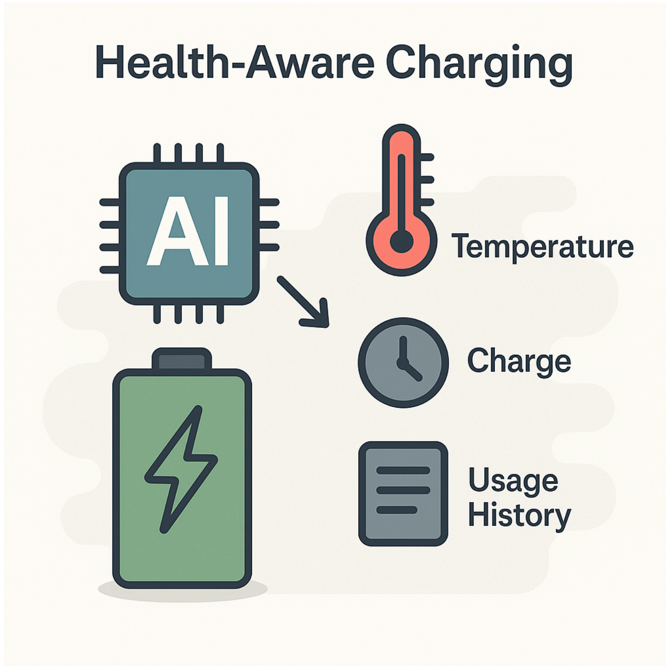

Figure 2.2 Health-Aware Charging

Health-aware charging strategies can **extend battery lifespan by 15–40%**, reduce thermal degradation, and prevent early failures.

Energy Trading AI Agent

The Energy Trading AI Agent is an autonomous decision-making system that determines when to charge or discharge battery storage systems based on real-time market prices. It learns to buy low (charging) and sell high (discharging) to participate in time-of-day tariffs, demand response, and wholesale energy markets to maximize revenue or reduce operating costs.

- **Model type:** reinforcement learning
- **Riverside use case:** SPT's sites can use AI to automatically decide when to store excess solar energy, sell energy back to the grid, or power electric vehicle chargers, depending on utility rates or grid demand in Southern California.

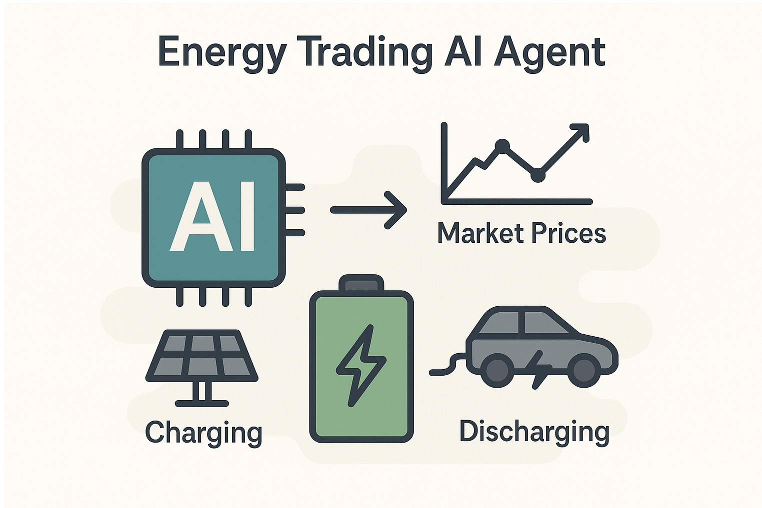

Figure 2.3 Energy Trading AI Agent

Energy arbitrage with AI agents can improve profitability by **20–40%** over rule-based or static strategies, depending on market volatility.

Predictive Maintenance Scheduler

The Predictive Maintenance Scheduler uses AI to monitor the battery system's performance and predict when a failure, fault, or performance drop will occur. Instead of waiting for components to fail or using fixed schedules, the system uses real-time data (temperature, capacity, cycle count) to schedule inspections or replacements, increasing uptime and safety proactively.

- **Model type:** Time-series forecasting or regression (e.g., LSTM, XGBoost)
- **Riverside use case:** Reduces downtime of SPT's battery-powered charging stations by flagging issues before they happen, especially important during high-demand seasons like summer.

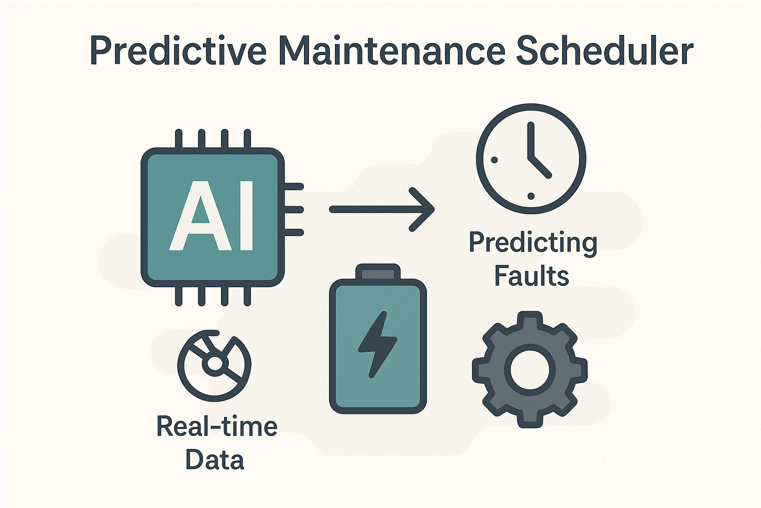

Figure 2.4 Predictive Maintenance Scheduler

Predictive maintenance with AI can **reduce unexpected failures by 30–50%** and **lower maintenance costs by up to 25%**.

Microgrid Collaboration

Microgrid Collaboration uses AI to coordinate how batteries across multiple stations share energy smartly. Instead of managing each battery separately, the AI predicts demand, storage levels, and solar output across the local microgrid and balances charging/discharging to improve efficiency, reliability, and grid stability.

- **Model type:** Multi-agent systems, graph neural networks (GNN)
- **Use case in Riverside:** As SPT expands its solar + battery EV stations in Riverside, AI could optimize how each station contributes power to the grid or supports neighbors during peak demand or outages.

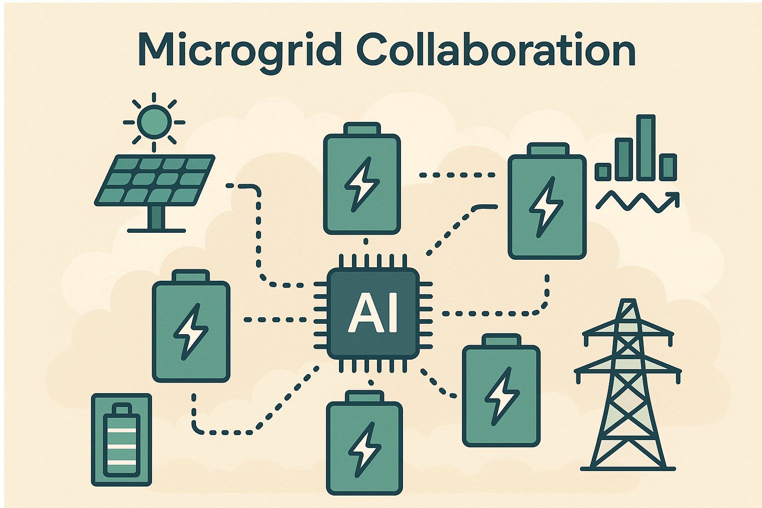

Figure 2.5 Microgrid Collaboration

Coordinated microgrid energy sharing can reduce energy costs by **15–30%** and improve battery system utilization by **20–40%**.

Model & Implementation

While I found some data from online research to support the idea, moving from theory to practice is also necessary. Now, instead of using a stat number from online, let's find a dataset and predict data from the existing dataset.

The dataset I'm using here is Battery Remaining Useful Life (RUL)

Battery Remaining Useful Life (RUL)

Predict the RUL of batteries by features based on voltage and current.

https://www.kaggle.com/datasets/ignaciovinuales/battery-remaining-useful-life-rul

This is the overall visualizations for the data (Figure 3.1):

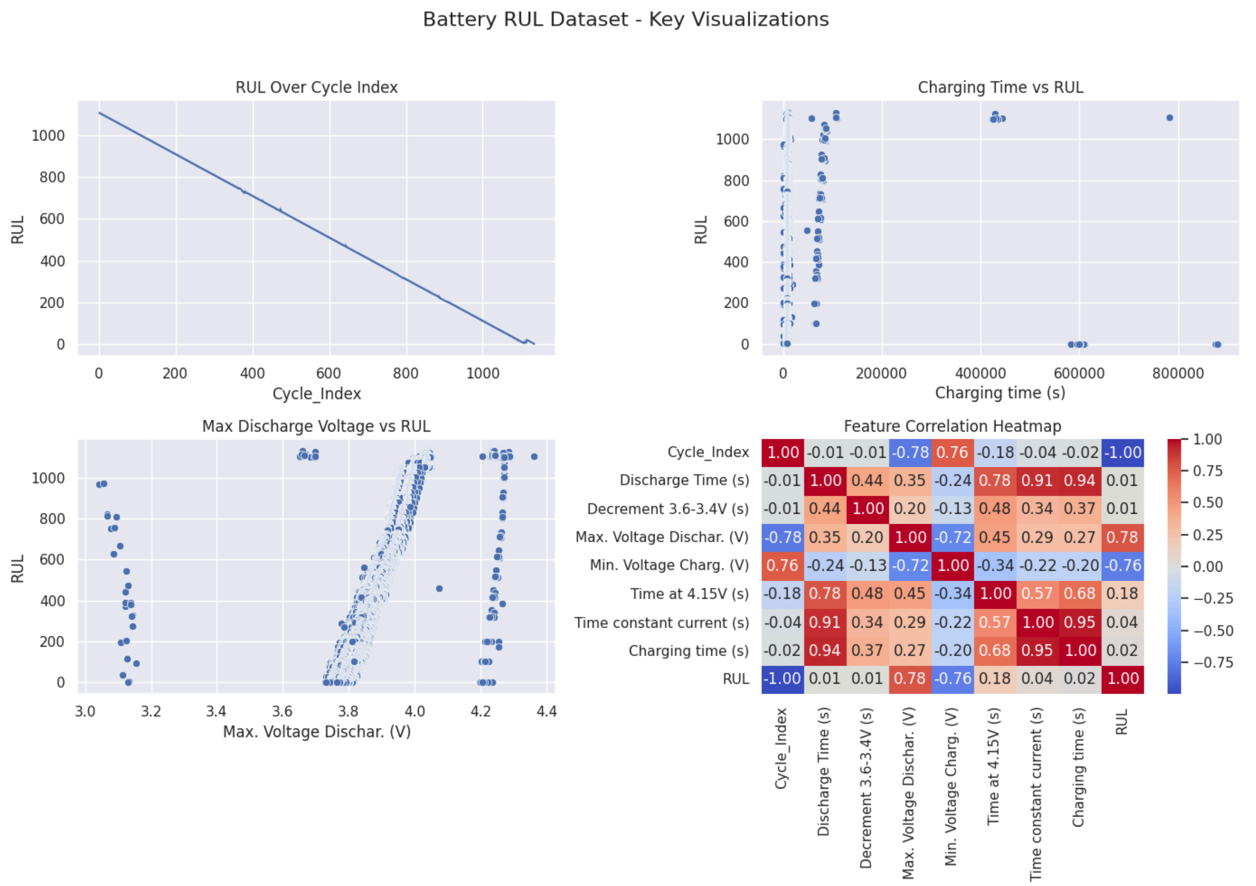

Figure 3.1 Overall visualizations for the data

For this sample model showcase, I run 2 models for two features:

- XGBoost for Health-Aware Charging
- LSTM for Predictive Maintenance Scheduler

XGBoost for Health-Aware Charging

The first model I run is for Health-Aware Charging using XGBoost, which integrates AI technology to adjust the charge rate, depth, and duration based on the battery's current condition, temperature, and usage history.

Overall, I got the result of:

```
XGBoost Model Mean Squared Error: 5.35
XGBoost Model R^2 Score: 1.00
```

And here is the plot for predicted vs actual (Figure 3.2):

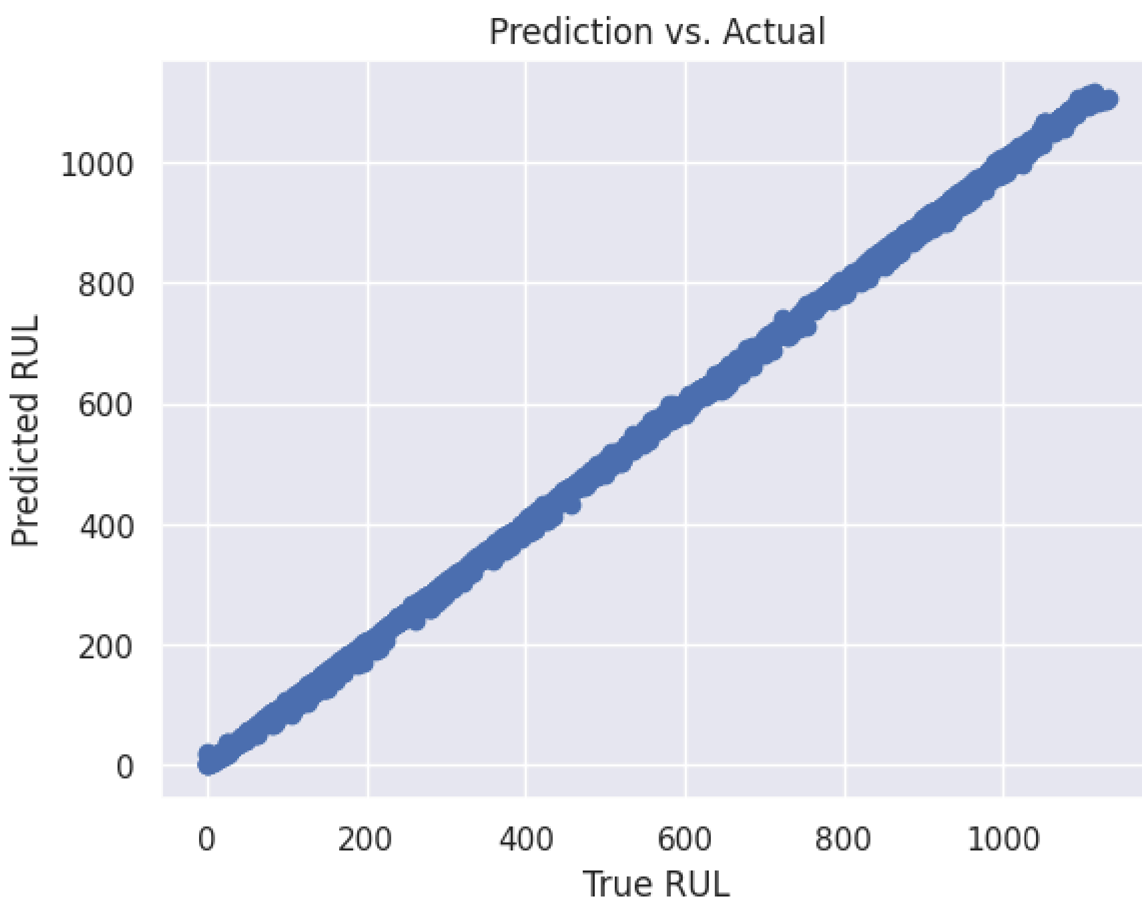

Figure 3.2 Plot for XGBoost, Predicted vs Actual

From both the running result and the plot, we can see that XGBoost performs well on this dataset. The value of R^2 is perfect 1.0, which is very rare to see, but based on the plot, it shows that currently there is no risk of overfits.

RMSE is 5.35 means there are 5.35 RUL units off on average, which is also good.

LSTM for Predictive Maintenance Scheduler

The second model I run uses LSTM for Predictive Maintenance Scheduler, which uses AI to monitor the battery system's performance and predict when a failure, fault, or performance drop will occur.

Although for both models the input and output are the same (input X is all features except the target, and Y, the target, is RUL), XGBoost captures static relationships while LSTM captures temporal patterns.

After running the model, I got the result of:

```
LSTM Model RMSE: 3.76
LSTM Model R^2 Score: 1.00
LSTM Model RMSE: 3.76
LSTM Model R^2 Score: 1.00
```

And here is the plot predicted vs actual (Figure 3.3):

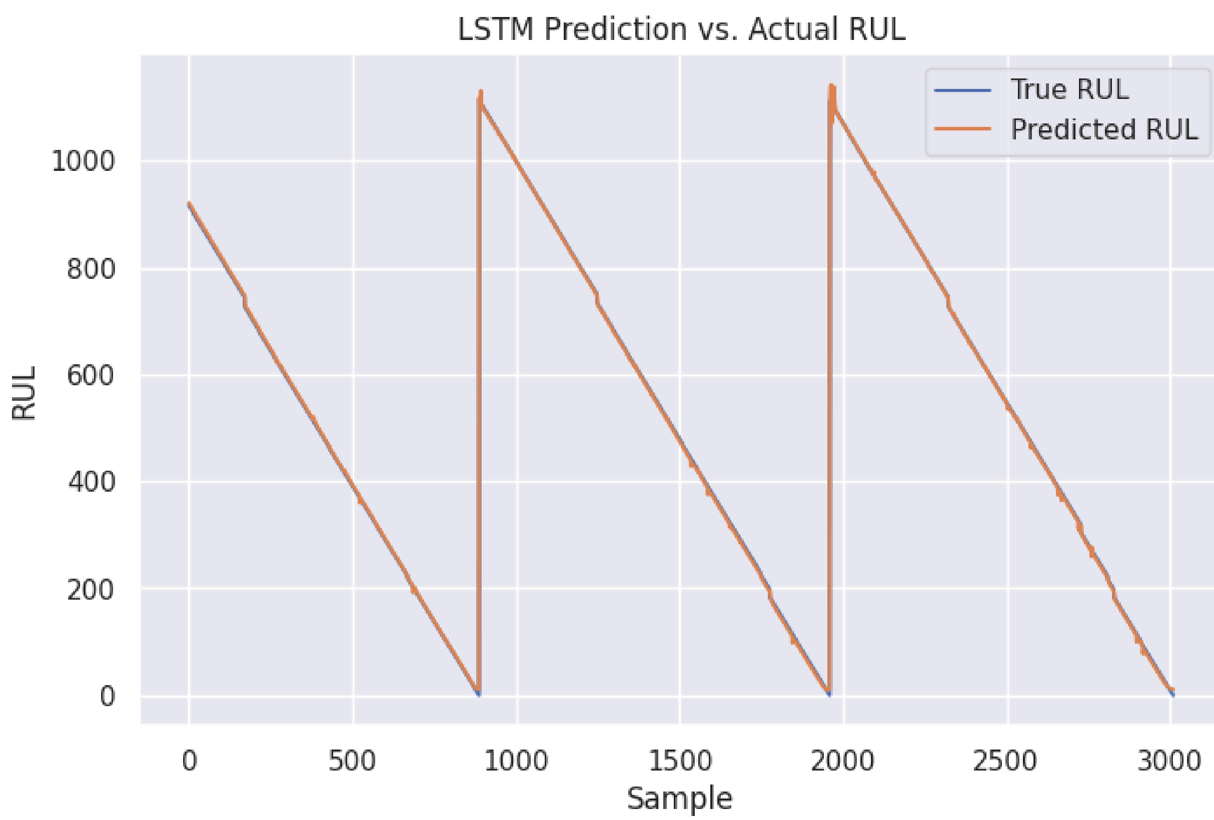

Figure 3.3 Plot for LSTM, Predicted vs Actual

From both results, the R^2 are still very high and even the same as XGBoost, the curve Predicted vs Actual is also perfect. A RMSE of 3.76 means there are fewer than 4 units off on average, which is very accurate.

For more details, refer to the source code in a notebook. Overall, both models are doing very well on this particular dataset.

Conslusion

My project introduces an AI-driven solution to optimize battery storage systems by balancing cost, lifetime, and sustainability. Using XGBoost and LSTM models, we can accurately predict battery health and average battery life (RUL), enabling smarter energy decisions. This system supports cleaner, more efficient infrastructure, particularly for solar electric vehicle charging in Riverside, and can be expanded to broader smart grid applications.