Reinforcement Learning Applied to the Shoals Marine Laboratory Smart Grid

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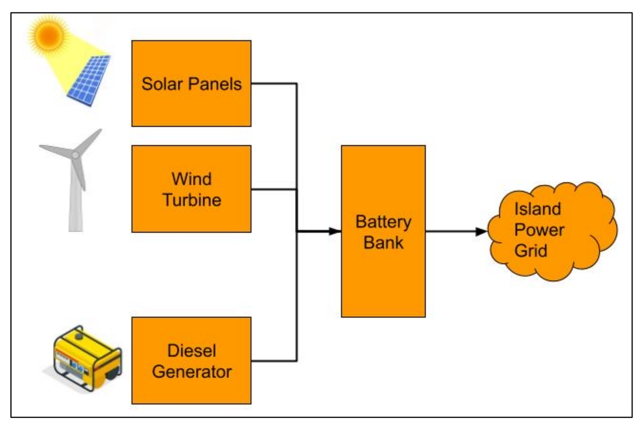
Abstract

- The Shoals Marine Laboratory (SML) is a remote island lab utilizing an isolated power grid with the goal of solely using renewable energy, with a diesel generator as backup.
- Minimizing generator use and maximizing battery longevity is a complex task because of unpredictable environments and electricity demand.
- Reinforcement learning (RL) can be applied to this problem to improve generator usage beyond the naive policy the SML currently uses.
- Different underlying RL models are compared and evaluated in this project, with the linear spline approximation providing the best results.



A simplified diagram of the SML power grid

Reinforcement Learning

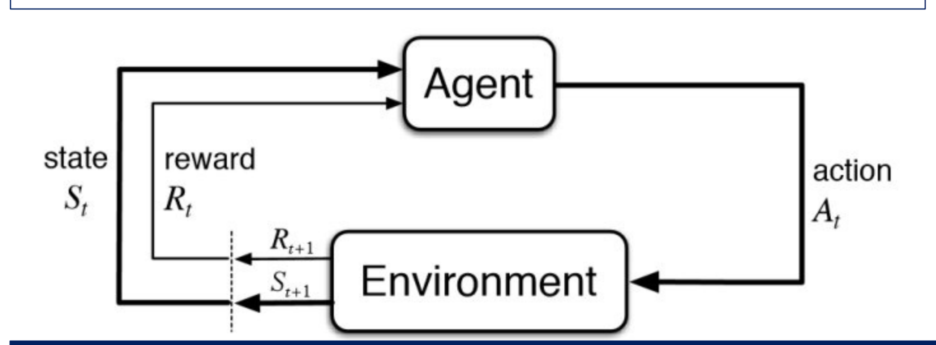
- RL is a machine learning technique where an intelligent agent takes actions in an environment to maximize its notion of cumulative reward.
- The environment is modeled as a set of possible states and actions, and the agent receives a reward for each action it performs.
- In this model, the states include the battery charge, whether the generator is on, and the island's power demand. The action is if the generator will be turned on.
- The value function is used to quantify the perceived value of a state and is what the agent uses to choose actions. The goal is to choose actions leading to states of high value.
- Approximating the value function is the primary problem that must be solved to choose an optimal action. From a value function, a policy (mapping from state to action) can be created for the agent to choose an action from any state.

$$\mathcal{S} = [0.0, 100.0] \times \{0,1\} \times \mathbb{R}^+, \quad \mathcal{A} = \{0,1\}$$

$$v(s) = \max_{a \in \mathcal{A}} \{r(s,a) + v(f(s,a))\}$$

$$\pi(s) \in \arg\max_{a \in \mathcal{A}} [r(s,a) + v(f(s,a))]$$

- $\mathcal{S}$: set of possible states
- $\mathcal{A}$: set of possible actions
- $v(s)$: value function
- $\pi(s)$: policy

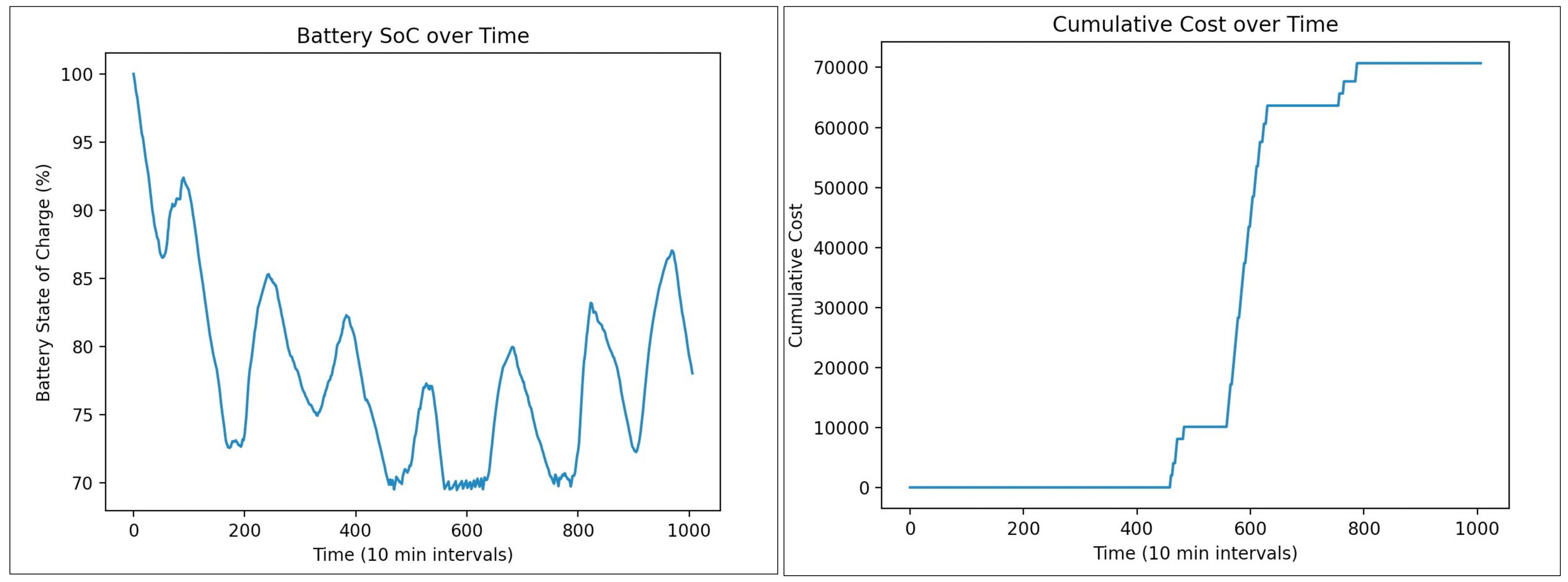


Data and Modeling

- All data used in this project was taken from the public SML website.
- Key variables to consider were the energy produced by solar, wind, and the generators on the island, along with the power usage from the battery bank.
- Fitted value iteration was used to approximate the value function using different features.
- Models using a neural net, linear spline, cubic spline, and radial basis functions were compared.

What the SML Currently Uses

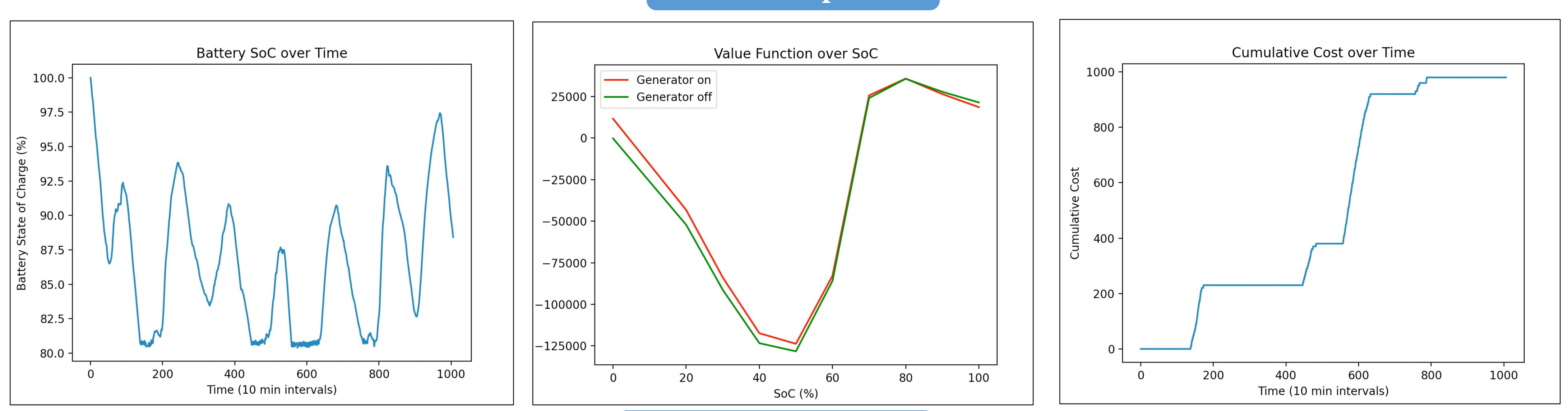
Run the generator when under 70% charge



Value Function Approximations

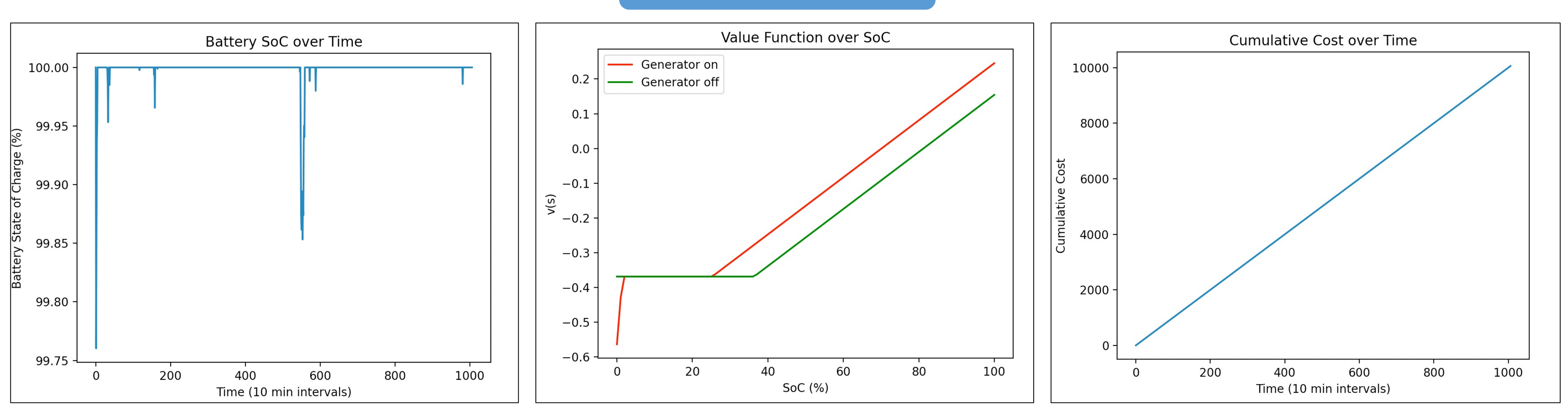
Linear Spline

Fit using 1 week of data



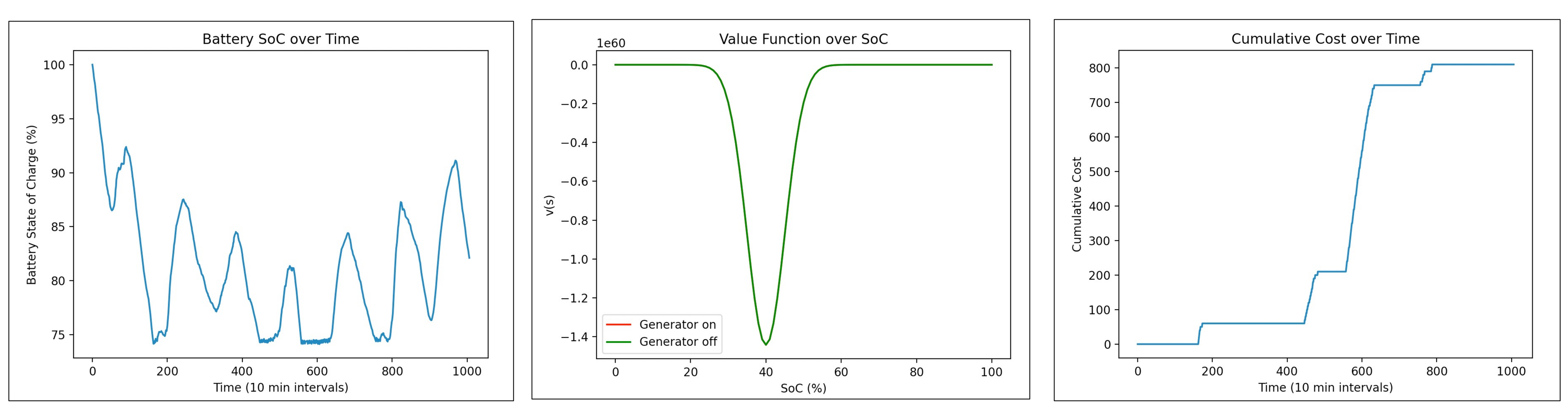
Neural Network

Trained on 1 day of data



Radial Basis Function

Fit using 1 week of data



Results

- The value functions produced by all model types generally trend upward with higher charge, which is expected.
- The high values for lower charge seen in splines and RBFs could be explained by a lack of training data in that region.
- The neural network was only trained on 1 day of data due to long training times.
- With a larger training set or adjustments to the structure of the neural net better results are possible.
- The linear spline has the most correct approximation, matching the intuition of the problem.
- In the simulation, the linear spline approximation beats the naive policy currently used by the SML.

Conclusions

- The linear spline model performed the best out of all models in simulations.
- RL was effective when applied to optimizing SML smart grid operation.
- Total "cost" was significantly reduced.

Future work:

- Expand model to use predictions of future power demand and generation, time of year (season or week number) as inputs.
- Include a reward for having surplus energy in model.

References

SML Data: https://sustainablesml.org/pages/systemList.php

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