FRI Data Science Project Competition 2024
Final report

Reverse-Engineering the Logic of an Electric Car Charging System with AI

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Abstract

As the complexity of systems deployed in real-world applications continues to grow, ensuring explainability of their decision-making processes becomes increasingly important. This overview dives into explanation of the decision-making processes of an electric car charging system managed by Siemens. Optimization of energy usage is crucial in making the grid more sustainable and efficient. We start with an initial dataset exploration, revealing discrepancies between the dataset and provided information about the system. We establish a baseline model on a subset of data, successfuly recovering ground truth rules, governing the grids behavior. Employing two contrasting approaches in the form of deep neural networks and logic tensor networks, we show the importance of fastcharger station power and provide a revised set of rules and thresholds, governing the system. We argue for benefits of employing hybrid AI approaches and propose suggestions for further work.

Keywords
Hybrid AI, Logic Tensor Networks, Neural Networks, Explainable AI

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Introduction

Current global energy consumption necessitates the exploration of optimized usage strategies. These strategies aim to achieve a trifecta of benefits: enhanced sustainability, improved efficiency, and increased reliability within the energy infrastructure. By achieving these goals, we can mitigate the impacts of climate change and pave the way for a more secure and environmentally friendly future. The focus of this project relates to a power grid, which connects electric vehicle charging stations to three different power sources – solar panels, batteries and the public electric grid. Recognizing the constraints of the public grid infrastructure and the importance of maximizing battery lifespan, Siemens deployed a system that manages grid behavior and allocates power based on real-time supply and demand fluctuations (see Figure 1). However, the almost black box nature of the decision system makes it difficult to further improve and optimize its decision making process.

Our goal with this project is therefore to explain the decision-making process that governs the behavior of the grid by analyzing the data related to the grid's past performance. We approach the task by first analyzing initial proposition of grid governing ruleset provided to us by Siemens. We try to recunstruct and verify the proposed ruleset and potentially improve and expand upon it. In order to do so, we compare and contrast two different approaches. First approach, focused on accuracy, is based on traditional deep neural networks,

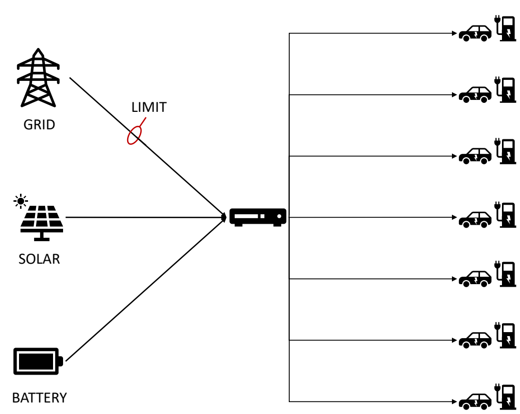

Figure 1. A visualization of the electric grid. A car using the charger gets energy from one of three sources – public electric grid, the solar panel, or the battery. Our goal is to uncover rules that govern the behavior of the elecric car charging system.

which were used to immitate the behavior of the grid. Various post-hoc explainability methods were used to gain insight into the networks behavior. Second approach was based on Logic Tensor Network architecture, which allowed us not only to better understand the model's decision making system, but incorporate domain knowledge into the learning process itself.

Dataset Exploration

Our dataset came in the form of 1 month worth of hourly data related to the system. It contains information about power demand of 8 different charging stations, 1 of which supports fast charging. It also contains information about power supply from the three sources - Solar panels, batteries and public electric grid. Additionally, battery state of charge is also provided.

In the first steps of the exploration, we examined the dataset in the light of the following ground truth rules, that were provided by Siemens:

- If **battery state of charge (SOC) $>$ 80%**, then E-cars charging is completely covered by the local battery.
- If **40% $<$ battery SOC%**, then if **grid power $>$ limit**, e-cars charging power is covered by local battery.
- If **battery SOC $<$ 40%** and:
  - **grid power $>$ limit**, then e-cars charging power is covered by local battery.
  - **grid power $<$ limit**, then local battery is charged from the grid.
- If **battery SOC $<$ 15%**, then battery discharging is stopped due to battery health.

Several drawbacks of the limited dataset in relation to the ground truth rules were discovered. Firstly, there are no instances where battery SOC would exceed 80%. This is not surprising since overcharging the batteries can negatively impact their lifespan. However, that makes the first rule impossible to recover. There are also several instances where despite power drawn from the grid exceeded the limit, the batteries were not fully utilized. Similarly, there are instances where, despite battery SOC $<$ 15%, the batteries were still providing power to the grid. In total, only approximately 16% of the data points were in line with the suggested ground truth. It is also important to note here that the ground truth that was given to us uses a single feature (battery SOC) to determine how the system operates. As it turns out later, it seems like this feature is not the only one that matters.

Baseline Model

With those shortcomings in mind, we first decided to prepare a subset of the data which strictly follows the provided ground truth rules. We then labeled the data according to where the energy was being drawn from, with the purpose of training a suitable baseline model. Decision trees were selected as the most appropriate model, mainly because of their simplicity and explainability. The nature of the model allowed us to extract exact rules and thresholds, governing the dataset. While classification accuracy is not the most important for the purpose of this project, it still provides a valuable insight into how well the model managed to capture the relationships in the data. After weighing the samples to account for class imbalance a decision tree of depth 2 was trained and tested on a random 80/20 train-test split of the dataset. The classifier, predicting the source of power on the cleaned dataset based only on battery SOC, achieved an accuracy of 71%. The resulting model can be seen in Figure 2.

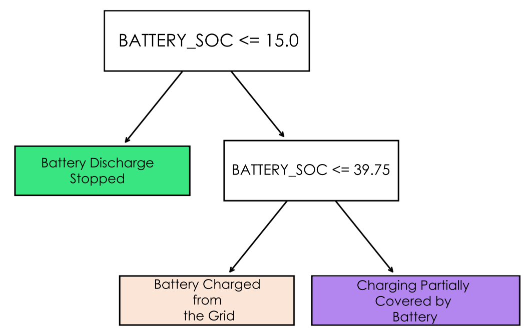

Figure 2. Baseline decision tree model, trained on the cleaned dataset. Both the 15% and the approx. 40% tresholds were retrived using only battery SOC as a feature.

While we were able to extract both the lower and the upper threshold, only battery SOC was used as a feature when training the model. This was done with the purpose of extracting the ground truth rules from the model. In order to assess importance of other features, the original dataset with all features was bootstrapped and decision tree models of maximum depth 2 were trained on the obtained datasets. Frequencies of feature occurances in the tree nodes indicated, that aside from battery state of charge, power, coming from the solar panels also plays an important role. This was further confirmed by feature analysis performed on a separately trained XGBoost model. After careful consideration, we determined that the influence was caused by mutual dependance on the time of the day. At times, when solar powar was at its peak, most charging stations were operating at full capacity, most likely since users of the grid were utilizing the charging stations, while they were at work. For that reason, solar power as a feature was excluded from further analyses.

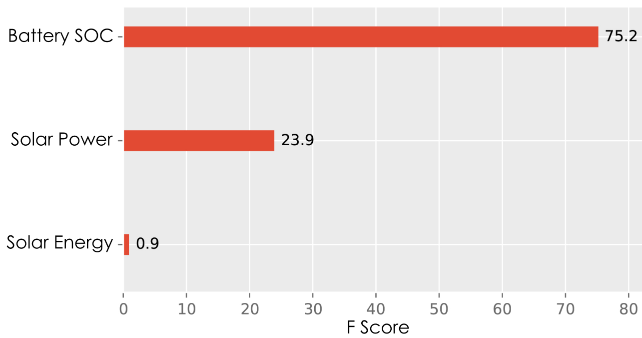

Figure 3. Feature importance based on gini index, extracted from XGBoost model. The battery SOC turned out to be the most important, followed by the solar power.

Deep Neural Networks

The initial baseline model, while offering a starting point, exhibited limitations in generalizability across the entire dataset with the overall accuracy reaching only 13%. This suggested potential inaccuracies within the provided ground truths. To address this, the first approach we explored was training a single-parameter neural network, with the purpose of first improving the suggested thresholds. A fully connected multi-layered perceptron was chosen for the model. Different architectures were tested, with a three-hidden layer structure (with 5, 2 and 7 neurons respectivelly) proving optimal. After correcting for class imbalance through the use of minority over-sampling technique, the configuration achieved a balance between rigidity and complexity, which allowed the model to learn two distinct thresholds. Counterfactual explainability method was employed to extract them. Notably, the lower threshold of 15% aligned with the ground truth, while the upper value turned out to be slightly higher at 47.5%. The accuracy of the model with revised thresholds can be seen in figure 4.

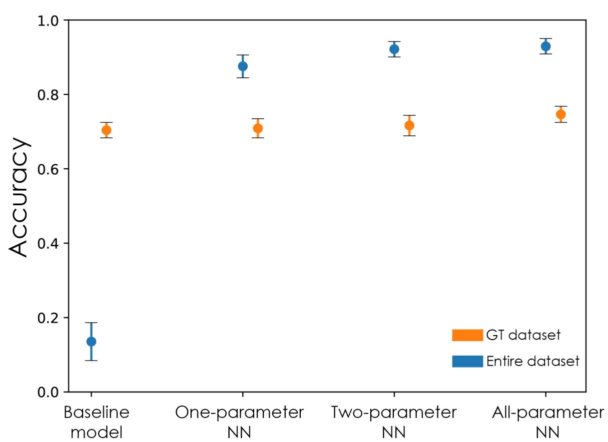

Figure 4. Accuracy of the four trained models on both the entire dataset, and the dataset that followed the proposed ground truths.

Next, a model incorporating all of the features was trained. Bootstrapping performed on the entire dataset once again revealed a jump in accuracy. To understand the most influenttial features, SHAP (SHapley Additive explanations) analysis was conducted. 300 samples were used to calculate SHAP values of 50 randomly selected samples from the original dataset.

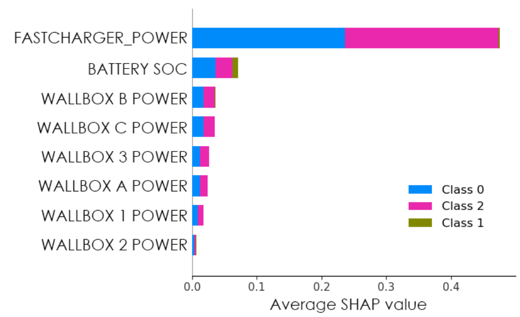

Figure 5. SHAP values indicating the importance of features in the neural network, trained on all parameters.

The results (Figure 5) revealed that fast charger power held significant importance forming the prediction of the model. With that in mind, a third iteration of the model was trained, this time only based on battery SOC and fastcharger power. Bootstrapping was again used to asses the accuracy of the model. Counterfactual method was again employed to reveal the boundaries between class predictions. The resulting plot can be seen in Figure 6

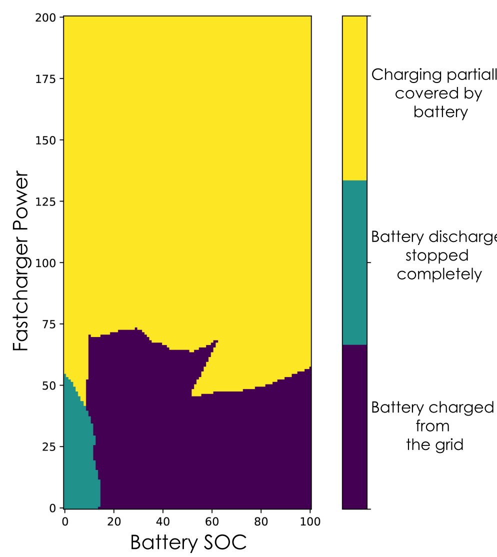

Figure 6. Two-parameter model thresholds revealing the relationship betwee battery SOC, fastcharger power and predicted class.

Logic Tensor Networks

Validation of neural network model

Continuing with the hybrid AI approach, we first set out to validate the results, obtained with the use of deep neural networks. For that purpose, we built a new network predicting source of power based on all input features. This model was then used as a foundation for incorporating logical constraints, using Logic Tensor Networks (LTNs).

LTNs allow us to both integrate and extract domain knowledge from the network. In our case, we pre-defined three rules, based on the ground truth thresholds related to the battery state of charge. The LTN then processed those rules and measured the compliance of the trained network against those rules, giving us a direct measure of quality of the proposed thresholds. Rule satisfaction, in this context, therefore refers to the degree of match between the model's predictions and the pre-defined rules. A value of 1 indicates perfect alignment, while a value closer to 0 signifies greater deviation. Following that approach, we were able to determine the satifaction level of 0.54 related to the originally proposed thresholds, while the thresholds proposed by the one-parameter deep neural network achieved a satisfaction level of 0.73. This result further validated, that the newly proposed thresholds better related to the given dataset.

Further validation was conducted using a two-parameter model that considers both SOC and fastercharger power. The specific rules were again taken from the deep neural network (see Figure 6). This two-parameter model with LTNs achieved a combined satisfaction level of 0.76, demonstrating both progress from the one-parameter model, while at the same time showing potential for further improvement.

Thresholds optimization

In the last section, we set out to independently derive the optimal rules and thresholds, employing the LTN approach. For that task we built 3 models, attempting to show that:

1. We can retrive the treshold if they are not specified.
2. It is possible to find better values for those tresholds.
3. It is possible to find other rules (thresholds), without relying on the ground truths.

While we initially considered an 80% SOC threshold based on GT, data exploration revealed that battery levels never actually reach this value. Additionally, instances satisfying the *completely covered by local battery* rule were scarce. Therefore, we focused on retrieving the more relevant 40% and 15% thresholds.

Model 1: Idealized Threshold Retrieval

The first model focuses on retrieving thresholds within a subset of data that strictly adheres to the pre-defined GT rules. It integrates the base LTN classification model with a regression task, creating an ideal environment for testing threshold retrieval.

Using this model, we successfully recovered values close to the expected 40% threshold and 15% SOC. Searching for these values individually yielded results closer to the GT values compared to searching for them together, likely due to increased loss with a higher number of rules.

Model 2: Refining Thresholds with the entire dataset

Building upon the first model, Model 2 applies the same concept to the entire dataset, not just the GT-adherent subset. This allows for potentially more accurate threshold values. While we still rely on GT-based labels, the inclusion of more data points (even those not adhering strictly to GT rules) helps refine the initial threshold values.

This approach resulted in a much more consistent retrieval of the 15% threshold and an improvement on the other threshold, reaching a value of 44%. Additionally, the model was able to achieve a much higher test accuracy of 94%.

Model 3: Rule Discovery with Regression

Model 3 eliminates dependence on the pre-defined GT rules by using only regression tasks. This reduces bias and allows us to validate the existence of thresholds based solely on data patterns. By guiding the regression task with logical constraints representing expert knowledge, this model demonstrates the ability to discover system rules.

Using this method, we again identified a threshold value of 44% for both $grid\ power > limit$ and $grid\ power < limit$ scenarios. This suggests that the specific relationship between grid power and the limit might not be crucial.

Well-defined rules enable us to find thresholds independently of GT. This leads to the conclusion that it is possible to discover other system rules by simply defining expert knowledge as a set of constraints that guide the regression task.

Discussion

While the ruleset proposed by Siemens proved to be a valuable starting point, our investigation revealed inconsistencies between the ruleset and the dataset. With two contrasting approaches, we were able to show that it is possible to both improve the existing rules, and discover new ones in the process. Using traditional deep neural networks we showed, that while the state of charge of the battery is very important in predicting the system's behavior, other factors also play a big role. By training a model that was able to immitate the behavior of the system with more than 92% accuracy, we were able to uncover the more complex relationship between battery state of charge and power, being delivered to the fastcharging station. Through the use of LTNs, we were able to verify and independently confirm the improvement made to the initially proposed ruleset. At the same time, we prepared a platform, allowing for further integration of domain knowledge and restrictions, related to the physical requirements of the system. Though great improvement has been achieved in the context of understanding and explaining the behavior of the system, plenty more opportunities for further work presented itself during the course of the project, including potential of integration of more complex rules during and after the learning process of the LTNs. More complex rules could potentially reveal even more detailed relationships, governing the behavior of the system.