

MACHINE LEARNING APPLICATIONS FOR SMART INVERTERS





Machine Learning Applications for Smart Inverters

ABSTRACT

Machine learning algorithms have gained significant popularity in recent years for their ability to find relationships between complex inputs and outputs of all kinds, from image recognition to medical applications and beyond. This white paper will discuss potential machine learning applications for distributed energy resources and smart inverter settings.

As distributed energy resources (DER) like solar photovoltaic (PV) systems are increasingly adopted, they are also manufactured with more complex on-board controls. Correctly configuring and safely interconnecting these resources to the larger electrical system is increasingly difficult due to the sheer number of variables (e.g. weather or customer behavior, distribution system characteristics, etc.). Machine learning (ML) and artificial intelligence (AI) algorithms are uniquely positioned, and perhaps necessary, to manage DER due to their affinity for solving such multi-dimensional problems.

A major component of decarbonization efforts is ensuring the energy system is well-positioned to accommodate renewable energy generation sources. This includes safely integrating DER into microgrids, the distribution system, and the bulk transmission system.

ML techniques model complex systems (like the grid) as a black box, instead of requiring a complete physical model full of scientific equations. This can be particularly useful in helping utilities integrate newly available “smart inverters” where their responses are less predictable and entirely software-defined. Moreover, they can also detect differences in expected device behavior whether they be positive (in the case of DER providing grid services) or negative (resulting from errors in utility record-keeping).

Generally, a solar inverter converts as much of the DC power generated by solar cells as possible into AC power compatible with the grid. Smart inverters, which have recently become commercially available, have additional features, some which allow them to react to changes in voltage and frequency. If configured correctly, these functions can allow the grid to receive more PV energy than previously allowable. However, if they're not correctly set up they can cause power quality issues for other customers or cause the PV plant to produce significantly less energy than it would have normally.

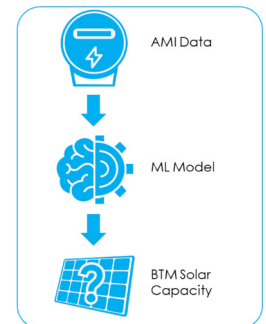
WHAT IS MACHINE LEARNING?

Machine learning (ML) is a form of advanced data analysis that allows computers to find relationships between complex inputs and outputs based on large amounts of previously collected data. For example, machine learning algorithms can take in an image and convert it to a caption of the subject in the image. With enough data, ML algorithms can be trained to build models that can predict relationships between inputs and outputs in enormously complex systems. PV plants, and the grid they interconnect with, are systems that could benefit from ML analysis techniques and algorithms.

UTILITY RECORDKEEPING

As inverter-based DER adoption becomes more prevalent, it will be important for utilities to verify the following:

- Inverters are connected to their system and functioning properly.
- Inverter size is correct in utility records.
- Inverters are following the smart inverter function they have been assigned.



Often, inverter generation and household load are mixed and read by a single meter. The mixing of generation and load makes it difficult to decouple the inverter and verify that it is working as intended. With support from EPRI's AI initiative, EPRI has conducted research on ML techniques to analyze the mixed load and generation data and identify whether an inverter exists at the site as well as the inverter size. Using ML techniques, EPRI was able to accurately differentiate homes that have solar from homes that do not have solar based on only the aggregate load. Even in cases of abnormally high load or abnormally low solar, ML algorithms trained on appropriate data can identify whether a customer has a behind-the-meter (BTM) generation source. To test this, EPRI scaled solar generation to be 25% of its original amount and had a 99% accuracy at detecting BTM PV.



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The amount of reactive power and curtailment available for an inverter typically depends on the inverter size, which requires accurate recordkeeping of the currently installed inverter for each customer. If the recorded capacity is inaccurate, assumptions about the way the inverter may operate and impact the system would be incorrect. Muddying the waters further is the fact that any historical generation data are likely mixed with load.

a new challenge in that the best settings for these functions often depend on many variables and are unique to each service territory. Not only that, but the potential impacts of these settings—such as active power curtailment—are also complex reactions. With so many interacting variables, machine learning and artificial intelligence algorithms may be needed to sufficiently model the system.

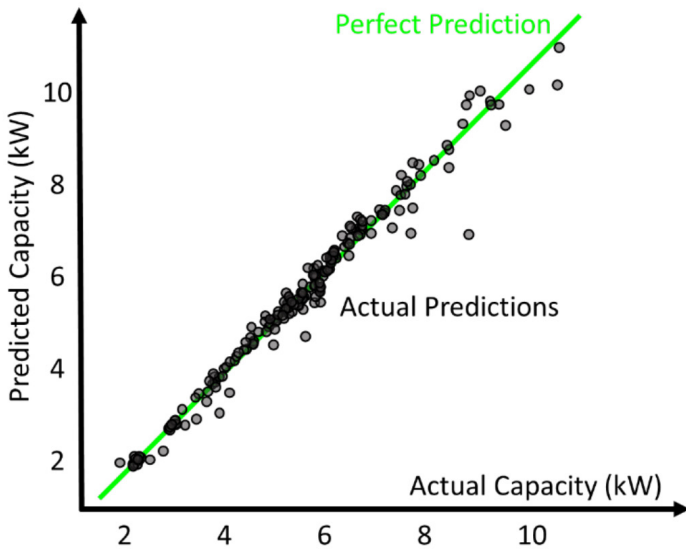


Figure 1 – Predicted vs. Actual BTM PV Capacity Based on Aggregate Load Data

EPRI was able to use household aggregate load and generation along with known system sizes to train an ML algorithm to predict the BTM system size. The model was created using a random forest algorithm trained with net load data and known BTM system sizes associated with it. With only timestamped aggregate load data, EPRI was able to predict the BTM PV system size with 97% accuracy (see Figure 1).

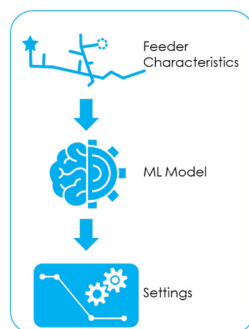
Curve-based settings allow inverters to have a different output based on the measured grid voltage. The parameters for these settings often allow operators to choose a setpoint, a slope, and a deadband independently of one another. Research to date has attempted to optimize these parameters in a brute-force fashion—repeated grid simulations varying the individual parameters to perform a sensitivity analysis.

This problem has many dimensions to consider. There are parameters themselves, the system the DER is connected to, the location of the DER on that system, and the time-varying aspect of the optimal solution.

ML algorithms can be useful to help solve these multidimensional problems. For example, it may not be necessary to brute-force simulate every possible combination of volt-var curve parameters for every node on every feeder. Instead, a volt-var curve model could be created that takes in node characteristics and outputs an assigned volt-var curve. The added intelligence provided by the model could be implemented in the inverter, using only variables locally known to the inverter, or within a utility’s operations center where the entire system is visible. EPRI is investigating both techniques. Preliminary results suggest that ML assisted decision making at the inverter can outperform default curves, and decision making based on the fully visible system may yield results close to optimal with less computational and engineering effort than the brute-force technique.

SETTINGS

There are several functions available to smart inverters, including some functions that work simultaneously with others—creating a nearly infinite suite of configuration options available to customers and grid operators. This availability allows for incredible customization, but also poses

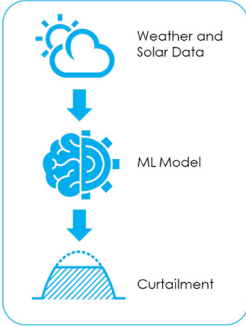


An alternative is to control the inverter in real time using a distributed energy resource management system (DERMS). As the DERMS makes decisions in real time, ML techniques could be used to help tune the parameters of the model. Reinforcement learning, a current popular technique that allows ML algorithms to improve over time, may be applicable here. For example, reinforcement learning could be used to provide intelligence to the DERMS, creating a penalty function when the measured results don’t align with the predicted results—resulting in a better tuned smart inverter function model and better DERMS performance.



CURTAILMENT

Inverters typically deliver as much power as possible from the PV system they are connected to. However, smart inverters may curtail their generation to allow for more reactive power to be generated or to prevent voltage issues caused by excess generation. By moving the operating point of the inverter away from the maximum amount of power available to some curtailed amount, it becomes difficult to know how much power would have been available without the curtailment. This can make it difficult to understand potential adverse impacts of releasing the curtailment command—how much power will be available when the command is lifted? It is particularly important to know the power available without curtailment if DER owners are being compensated for lost production due to utility-issued curtailment commands.

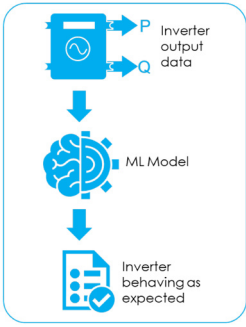


This amount is a complex relationship of weather, functions chosen, PV system conditions, and grid conditions. Traditionally, solving for the available power requires a significant amount of instrumentation at the DER site to capture as much weather and electrical data as possible. Using this instrumentation, a physical model of the DER site can be created in modeling software to estimate potential production. The physical model requires knowledge of DER physical site layout, electrical layout, and device (such as inverters or solar panels) model numbers. ML algorithms and other statistical models are useful to model the plant based on significantly less information, requiring less instrumentation, cost, and effort to build the model.

PV systems are typically linear combinations of sunlight available, temperature, and windspeed. Using data where the system is not curtailed, a model can be trained using these inputs to predict the power available. This model could then be used during time periods when the system is curtailed to predict the amount of curtailment and amount of power available when the curtailment command ends. EPRI has used this technique in past research, which had as good or better accuracy as the physical model—with significantly less effort and documentation to create.

VERIFICATION

FERC 2222 allows DER to act as service providers for the grid, which will require PV plant owners as well as system operators to have confidence that an inverter is providing a particular service intentionally and in the correct way. For example, if a PV plant is commanded to not produce above a certain amount of power, how does an operator know if the PV plant is curtailing its power or simply in a cloudy period?



EPRI has developed an online tool (available for members at der.epri.com) that members can use to verify that their functions are behaving appropriately (see Figure 2). If the user knows the smart inverter function assigned to the inverter, they can upload their own data and the tool will use traditional analytics to verify whether the inverter is following the function it is supposed to. In addition, if the data are clearly not following the function that they should be, the tool uses ML techniques to predict the function it thinks the inverter is following and reports that back to the user.

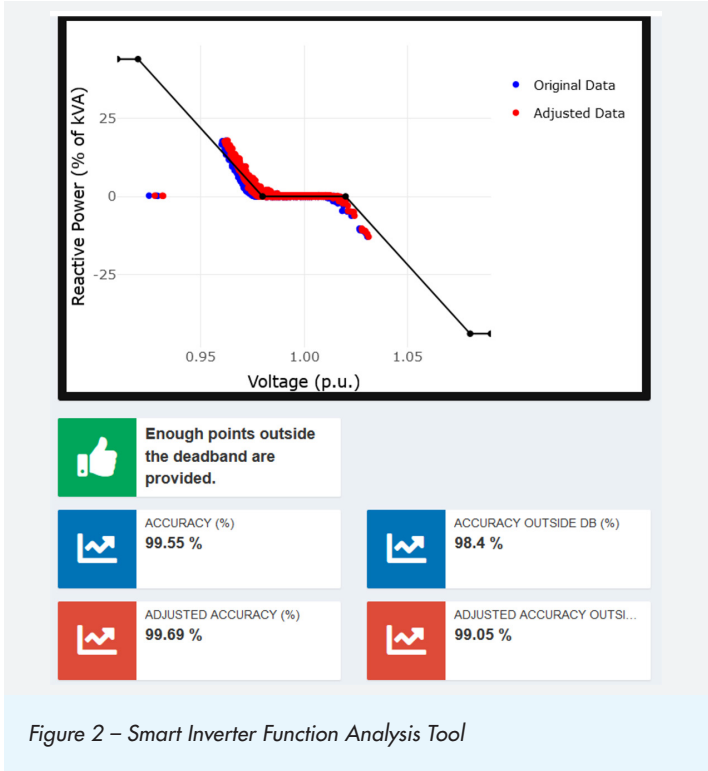


Figure 2 – Smart Inverter Function Analysis Tool



CONCLUSION

ML and AI algorithms in recent years have affected nearly every industry, and there are significant opportunities for these algorithms to be deployed to help improve utility operations—particularly for adoption of DER and smart inverters. These algorithms’ ability to find complex relationships that may be difficult or impossible to physically model has great potential value in the utility space where relationships between grid conditions and the devices connected to the grid are enormously complex.

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Integration of DER

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