# Interpretable Machine Learning for Power Systems: Establishing Confidence in SHapley Additive exPlanations

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***Abstract*—Interpretable Machine Learning (IML) is expected to remove significant barriers for the application of Machine Learning (ML) algorithms in power systems. This letter first seeks to showcase the benefits of SHapley Additive exPlanations (SHAP) for understanding the outcomes of ML models, which are increasingly being used. Second, we seek to demonstrate that SHAP explanations are able to capture the underlying physics of the power system. To do so, we demonstrate that the Power Transfer Distribution Factors (PTDF)—a physics-based linear sensitivity index—can be derived from the SHAP values. To do so, we take the derivatives of SHAP values from a ML model trained to learn line flows from generator power injections, using a simple DC power flow case in the 9-bus 3-generator test network. In demonstrating that SHAP values can be related back to the physics that underpin the power system, we build confidence in the explanations SHAP can offer.**

***Index Terms*—Interpretable machine learning, machine learning, power systems, sensitivity analysis.**

## I. Introduction

POWER systems are extremely complex high dimensional systems, the complexity of which is only set to increase with the connection of renewable energy sources and inclusion of other energy vectors such as heating and transportation. Understanding complex power system phenomena in this context is crucial for ensuring continued reliable power supply. In recent years, many Machine Learning (ML) applications to predict the behaviour of various aspects of power systems have been developed—some of which are summarised in [1]. While these black-box ML algorithms have shown good accuracy and computational savings, their applicability to mission-critical infrastructure such as power systems is limited due to absence of trustworthy explanations.

The premise of *interpretable* ML—an emerging area of research—is to provide detailed explanations of ML model predictions in order to enhance confidence in the model predictions. Among the post-hoc ML model interpretability methods, which [2] presents concisely, SHapley Additive exPlanations (SHAP) has gained some initial traction in power systems, as [3] reviews. The focus of the limited number of applications in literature, however, usually centre around applying SHAP, rather than analysing the method itself.

SHAP [4] is model agnostic (i.e., can be applied to different types of ML models) and is of the class of additive feature attribution methods; meaning that it attributes an effect of a feature $x_i$ on the prediction of a model $f(\boldsymbol{x})$.

Such methods construct a simple additive *explanation model*, $g$—which is a linear function of binary variables—to represent the complex *original model*, $f$. In the SHAP framework, the explanation model is expressed as a "conditional expectation function of the original model" [4]. Simplified inputs $x'$ are used to map to the original input through mapping function $h_x$, where $x = h_x(x')$; ensuring $g(z') \approx g(h_x(z'))$, whenever $z' \approx x'$ and where $z' \in \{0,1\}^M$ and $M$ is the number of simplified input features. Thus an effect $\phi_i$ (where $\phi_i \in \mathbb{R}$) is attributed to each feature, the sum of which approximates $f(\boldsymbol{x})$ as per (1).

$$g(z') = \phi_0 + \textstyle\sum_{i=1}^{M} \phi_i z'_i \tag{1}$$

This quantification is based on Shapley values [5], which stems from game theory and describes the average marginal contribution of a player to all coalitions in which the player contributes. The SHAP framework often incorporates approximate SHAP values for computational efficiency [4]. SHAP offers local explanations for a single point, which can be repeated for multiple points to achieve global interpretations. For more details, the interested reader can refer to [6].

This letter initially showcases SHAP interpretations as a tool for understanding power system ML models using a simple case study (Section II), and then establishes the capability of SHAP explanations to capture underlying physics of the power system—thus enhancing confidence in SHAP as an interpretability method (Section III). We achieve this by deriving Power Transfer Distribution Factors (PTDF) (i.e., the sensitivity of line flows to power injections) from SHAP values. In doing so, we seek to build confidence in SHAP as a tool for interpreting ML models.

## II. Using SHAP Values to Interpret ML Models for Line Flow Prediction: 9-Bus Case Study

Individual eXtreme Gradient Boosting (XGBoost) [7] regression models $f_{line,i-j}(x)$ are trained to predict the active power flow ($F_{line,i-j}$) on each line of the the 9-bus 3-generator test network (Fig. 1). This is achieved using a set

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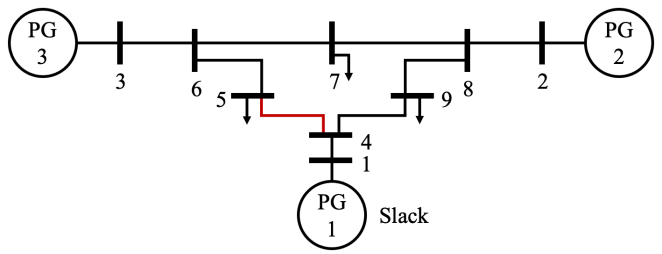


Fig. 1. 9-bus 3-generator test network with line 4-5 highlighted for analysis.

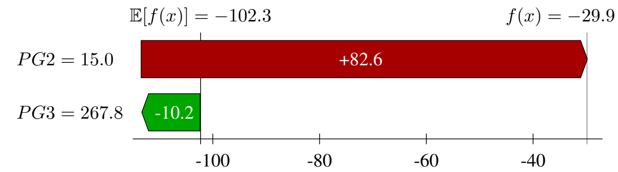


Fig. 2. Local SHAP explanation for $F_{line,4-5}$ showing how SHAP values of feature $\phi_i$ impact the move from model expectation $\mathbb{E}[f(x)]$ to final prediction $f(x)$ for a single operational scenario.

of input features $x$, $x \in \boldsymbol{P}$ for a simple DC power flow case, with a 75-25% train-test split. The parameters of the test network are taken from Matpower [8]. For the trained models, SHAP values are calculated (using the framework set out in [4], implemented in Python).

### A. Database Creation

To generate the database upon which the ML models are trained, samples of $PG2$ and $PG3$ are drawn independently from a uniform distribution in the range [0, 500] MW for a total of 1001 generation scenarios. For the sake of this case study, but without loss of generality, demand is assumed constant at 315 MW. $PG1$ acts as the slack bus. Following the execution of a DC power flow, the active power flow on each line is recorded ($F_{line,i-j}$) in the database. Since $PG1$ is the slack generator (and therefore not an independent feature), it is excluded from the database. The final database contains $PG2$ and $PG3$ as training features and $F_{line,i-j}$ as targets for all 1001 operational scenarios. Database available in [9].

### B. SHAP Insights: Analysis of $f_{line,4-5}(x)$

To gain insights into each ML model, the Tree SHAP algorithm (a polynomial time algorithm that leverages the tree structure [6]) is applied to each model. Analysis of a single local explanation and a global model interpretation of $f_{line,4-5}(x)$ is presented below. Similar analysis can be extracted for the remaining ML models $f_{line,i-j}(x)$.

*1) Local Explanation:* Local explanations provide the contributions of features (i.e. SHAP values, $\phi_i$) in shifting the model prediction from the model expectation ($\mathbb{E}[f(x)]$)—that would be predicted if we had no feature information—to the final prediction ($f(x)$) for a single operational scenario. Therefore the SHAP values ($\phi_i$) are given in the units of the variable being predicted. In this study, features are the $PG2$ and $PG3$ injections. An example of a local SHAP explanation for the model $f_{line,4-5}(x)$ is given in Fig. 2. For this particular operational scenario, the baseline model expectation ($\mathbb{E}[f(x)]$) for $F_{line,4-5}$ is $-102.3$ MW. $PG3$ setpoint is $267.8$ MW, which decreases the prediction by $-10.2$ MW ($\phi_{PG3}$)) from $\mathbb{E}[f(x)]$ to $-112.5$ MW. The setpoint for $PG2$ is $15.0$ MW, which increases the model prediction by $82.6$ MW ($\phi_{PG2}$). This results in the final prediction of $f(x) = -29.9$ MW. This is consistent with (1). Since $|\phi_{PG2}| > |\phi_{PG3}|$, $PG2$ has a greater effect in this scenario and thus is placed higher on the y-axis.

*2) Global Interpretation:* Global interpretations comprise of the local explanations for the entire training database, making them consistent. Analysis of SHAP values in the global frame assists in understanding the global model structure.

The global SHAP plot (Fig. 3) gives the SHAP value for each feature (x-axis) with respect to the feature value (color-axis). Features are ordered on the y-axis based on importance (defined here as the mean of all SHAP values for all operational scenarios). In this case, $PG3$ is found to have a higher importance than $PG2$ (note: this is the inverse to the local explanation given in Fig. 2 for that particular case, indicating how local sensitivity vs. global importance need not necessarily be the same). It can be seen that as $PG3$ increases, the SHAP values ($\phi_{PG3}$) decrease from positive to negative. This means that as $PG3$ increases the impact it has on $F_{line,4-5}$ goes from increasing the baseline prediction, to decreasing it. This is consistent with the theory of power flow when observing Fig. 1—where one would expect a higher $PG3$ setpoint to decrease $F_{line,4-5}$ in this simple DC power flow example. A similar trend can be seen for the SHAP values for $PG2$ ($\phi_{PG2}$)—although the impact is smaller than $PG3$, indicated by a smaller spread of SHAP values on the x-axis. The feature value is given on the color axis and is normalised based on the min/maximum feature value for trend identification, however the actual feature value (in MW) can also be extracted. This showcases how SHAP values can give some interesting insights about how power system features, here the power injections, affect our outputs of interest, here the line flows. This can be especially useful in more complex cases, where analytical relationships are difficult to extract.

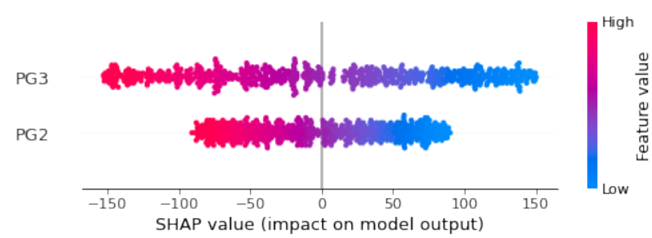


Fig. 3. Global SHAP interpretation for $F_{line,4-5}$. Each point for each feature is an operational scenario in the training dataset.

## III. Derivation of PTDF from SHAP Values

To show the link between SHAP values and the PTDF, we consider $f_{line,i-j}(x)$ to be a linear statistical model $f(\boldsymbol{x}) = \boldsymbol{w}^\top \boldsymbol{x} + b$ whose features ($\boldsymbol{x} \in \boldsymbol{P}$) are assumed to be independent. Here the features are the power injections $PG2$ and $PG3$.

**Theorem 1.** *The derivatives of the SHAP values $\phi_i(f, \boldsymbol{x})$, $i \neq 0$, associated with $f(\boldsymbol{x})$ yield exactly the PTDF of this network.*

*Proof.* Using Corollary 1 from [4], the SHAP values $\phi_i(f, \boldsymbol{x})$ associated with $f(\boldsymbol{x})$ are given by

$$\phi_0(f, \boldsymbol{x}) = b \tag{2}$$
$$\phi_i(f, \boldsymbol{x}) = \boldsymbol{w}_i(\boldsymbol{x}_i - \mathbb{E}[\boldsymbol{X}_i]),\ i \neq 0 \tag{3}$$

where $\boldsymbol{X}_i$ is the training data associated with the $i^{\text{th}}$ feature. Perturbing the $i^{\text{th}}$ feature (i.e., continuous regressor) yields

$$\frac{\partial \phi_i}{\partial \boldsymbol{x}_i} = \boldsymbol{w}_i. \tag{4}$$

Since $\boldsymbol{w}_i$ relates the sensitivity of line flow to the $i^{\text{th}}$ injection, the SHAP derivative is equivalent to a PTDF. □

For a definition and analytical derivation of the PTDF, the interested reader can refer to [10]. Strictly speaking, the result of Theorem 1 is only valid when the underlying statistical model is linear (or affine). However, ML practitioners often use models which have the capacity to be aggressively *non-linear*. SHAP can be applied in either case and as the trained models effectively still behave like *linear* models, (3)-(4) will remain approximately valid. To show this experimentally, we note that the sum across all SHAP values should yield a model with linear sensitivity to power injections, i.e., an approximate PTDF vector $\hat{\boldsymbol{D}}$, and a constant offset term $\epsilon$:

$$\sum_i \phi_i(f, x) = \boldsymbol{w}^\top(\boldsymbol{x} - \mathbb{E}[\boldsymbol{X}]) + b \approx \hat{\boldsymbol{D}}^\top \boldsymbol{P} + \epsilon. \tag{5}$$

By collecting a library of SHAP values $\Phi$ associated with a library of sampled injection values $\mathbf{P}$, a regression procedure can yield the PTDF approximation $\hat{\boldsymbol{D}}$:

$$\begin{bmatrix} \hat{\boldsymbol{D}} \\ \epsilon \end{bmatrix} = \mathbf{P}^+ \Phi, \tag{6}$$

where $(\cdot)^+$ denotes Moore–Penrose pseudoinversion.

Table I presents the analytical PTDF and the SHAP-based PTDF $\hat{\boldsymbol{D}}$ for the relevant buses for the case study in Section II. These experimental results support Theorem 1, showing that the derivatives of the SHAP values are equivalent to the PTDF for this network.

TABLE I
9-BUS 3-GENERATOR TEST NETWORK PTDF & SHAP.

| | True physical PTDF, $\boldsymbol{D}$ | | SHAP-based PTDF, $\hat{\boldsymbol{D}}$ | |
|---|---|---|---|---|
| Line | Bus 2 | Bus 3 | Bus 2 | Bus 3 |
| Line 1-4 | -1.0000 | -1.0000 | -0.9999 | -0.9999 |
| Line 4-5 | -0.3613 | -0.6152 | -0.3613 | -0.6151 |
| Line 5-6 | -0.3613 | -0.6152 | -0.3613 | -0.6151 |
| Line 3-6 | 0 | 1.0000 | 0.0000 | 0.9999 |
| Line 6-7 | -0.3613 | 0.3848 | -0.3613 | 0.3848 |
| Line 7-8 | -0.3613 | 0.3848 | -0.3613 | 0.3848 |
| Line 8-2 | -1.0000 | 0 | -1.0000 | 0.0000 |
| Line 8-9 | 0.6387 | 0.3848 | 0.6386 | 0.3848 |
| Line 9-4 | 0.6387 | 0.3848 | 0.6386 | 0.3848 |

## IV. Potential Applications of SHAP Framework

The main motivations for using ML are its capacity to provide explicit mappings of complex functions and accelerate computationally heavy tasks. One could use such a ML model directly, however they are often black-box and therefore difficult to interpret. To build confidence in the ML model and foster widespread use in the power system domain, understanding how the model makes predictions and identify potential relationships with power system physics is essential. Model interpretability techniques can be used to achieve this to either bolster existing knowledge, or infer new information about the power system. Ideally this should be standardised across the industry.

We believe that SHAP has the potential to be such a technique. This arises from the ability to look at local explanations, e.g., for a specific operating point, as well as global explanations, i.e., ranking feature importance for a model. Based on these explanations, we could (i) compare the performance of different ML models beyond pure accuracy as well as investigate their implicit biases, (ii) search for simpler operational rules derived from a ML model, (iii) improve the dataset generation by focusing on contradicting explanations.

For these processes to be effective, it is important to understand the characteristics of the explanation method, i.e., SHAP, itself. In this context, the ability to link SHAP and its explanations to physics (e.g., PTDF) is a desirable property. For a more complex case than the presented one, such links could reveal interesting insights and also help to gain confidence in both ML models and indeed SHAP as an interpretability method for power systems.

## V. Conclusion

Interpretable Machine Learning (IML) in power systems will become necessary to understand increasingly complex Machine Learning (ML) models used in academia and industry. For wide-spread adoption, confidence must be built in the interpretation method. Physical equivalence is one such way of developing confidence, which we have shown in this letter for SHapley Additive exPlanations (SHAP) and Power Transfer Distribution Factors (PTDF) in a simple DC power flow case. Extending from this linear case to more complex nonlinear problems will likely be a fruitful avenue of future research.

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