Gradient boosting models for photovoltaic power estimation under partial shading conditions

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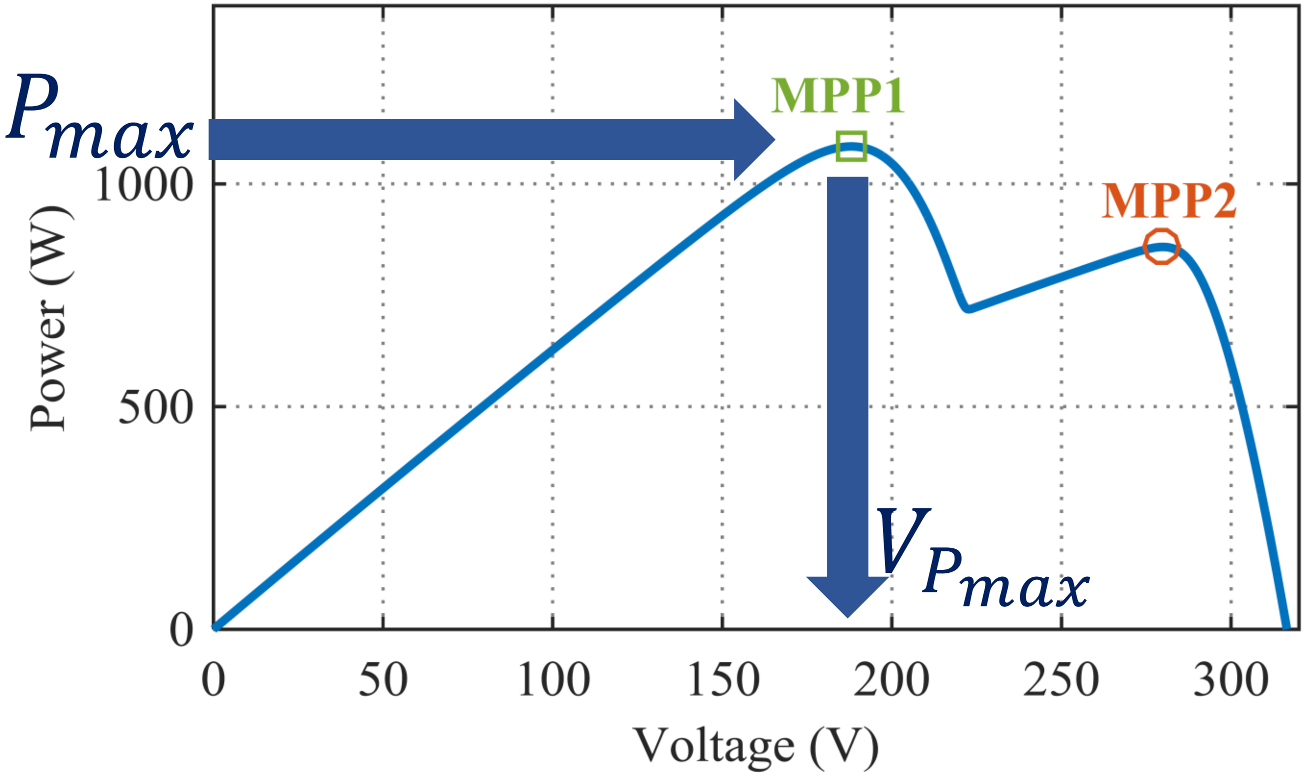
Partial shading in PV panel strings

Characteristic P-V curve of a partially shaded string



- Can have multiple **local** maximum-power-points (MPPs)
- As many MPPs as irradiance levels on a PV string
- Need to track **global** MPP $(P_{max}, V_{P_{max}})$ that provides maximal power output

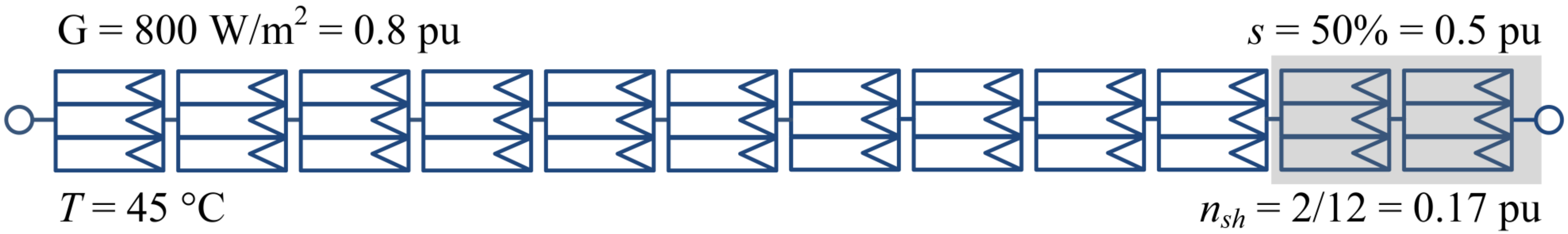
Main approaches Used

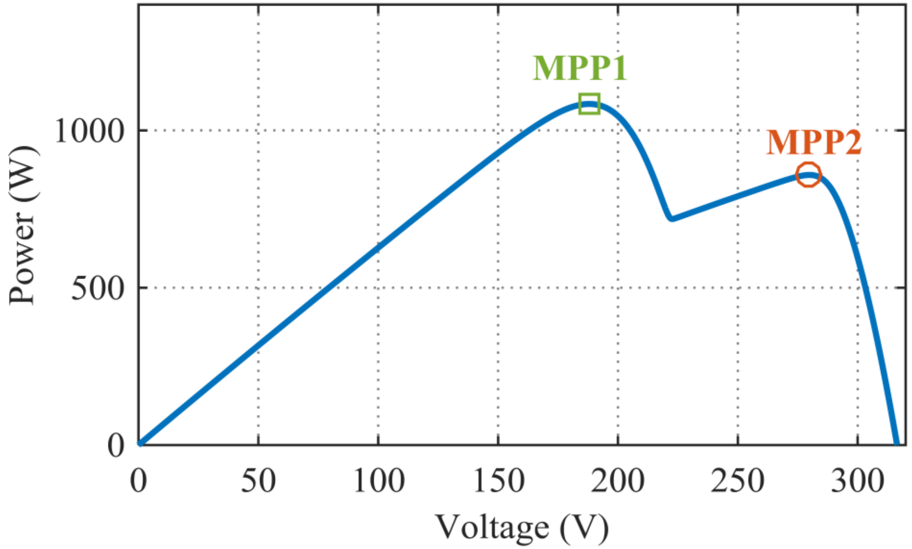
1. **Circuit-based** methods
   - Strong theoretical foundation
   - High accuracy
   - Require tedious simulations
2. **Heuristic** methods
   - Fast
   - Lower Accuracy

I. **Empirical formulas**
   - Simple formulation
   - Low accuracy

II. **Circuit equations**
   - Provide all MPPs
   - Good average accuracy
   - Occasionally high errors

Two irradiance levels (common case)



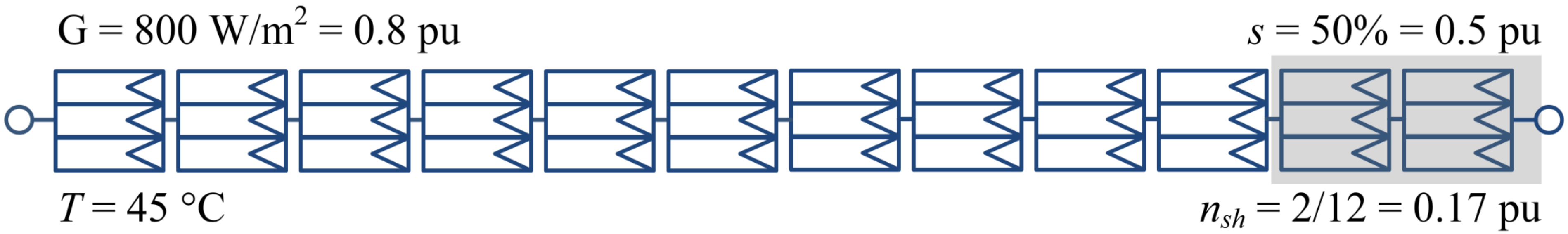


Operating conditions

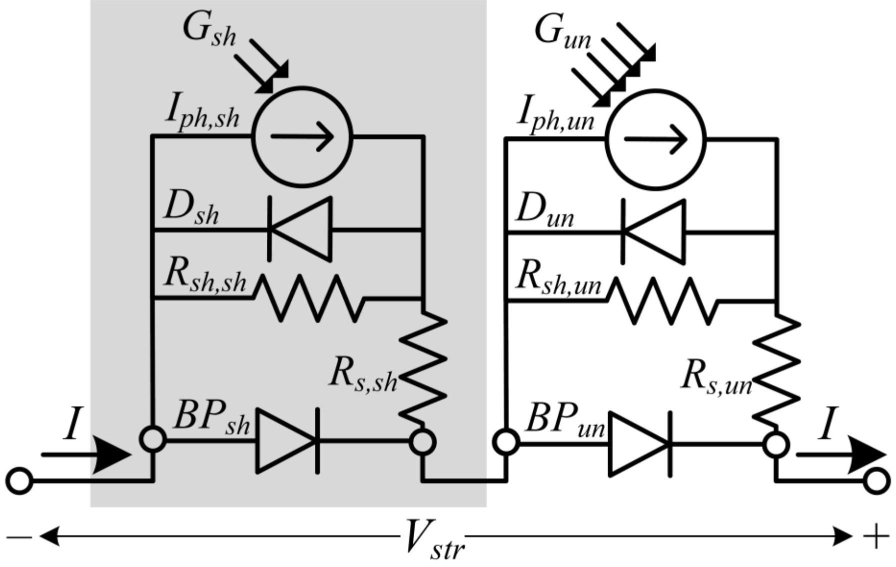
- G: irradiance (full)
- T: temperature
- s: shadow ratio
- n_{sh}: shadow extent

2 irradiance levels: P-V curve has up to 2 local MPPs

Equivalent circuit



- Simulate circuit under operating conditions to obtain P-V curve
- Find global MPP of P-V curve



Closed-form solution of the equivalent circuit

- Compute the local MPPs

$$MPP1 : \begin{cases} V_1 = N_{tot}[(1 - n_{sh})V_{mp}^T + n_{sh}\Delta V_D] \\ I_1 = GI_{mp}^T \\ P_1 = V_1 I_1 \end{cases}$$

$$MPP2 : \begin{cases} V_2 = N_{tot}[(1 - n_{sh})(sV_{mp}^T + (1 - s)V_{oc}^T) + n_{sh}V_{mp}^T] \\ I_2 = sI_{mp}^T[1 + \lambda(1 - nsh)] \\ P_2 = V_2 I_2 \end{cases}$$

- Then find global MPP

$$global\ MPP : \begin{cases} P_{max} = max\{P_1, P_2\} \\ V_{P_{max}} = \{V_{i^*} : i^* = \arg\max_{i \in \{1,2\}} P_i\} \end{cases}$$

Modelling using machine learning

- Train on examples of
  input (feature) $[G, T, s, n_{sh}]$ &
  output (target) $[P_1, V_1, P_2, V_2, P_{max}, V_{P_{max}}]$ vector pairs

- **Goal**: Better approximate $(P_{max}, V_{P_{max}})$ than closed-form equations

- Also included **'intermediate targets'** of MPP1 (P_1, V_1) & MPP2 (P_2, V_2)
  2 of the 3 models we train use these

Modelling the circuit using machine learning

- Models examined: **Gradient Boosted Trees** (Regression & Classification)

  FW will include Random Forests (initial results favourable) & Neural Networks

- In every case, **consider P & V independent**

  Correlation very low - verified by initial experiments

  FW will include relaxing this assumption

Model 1: Direct modelling of global MPP

- Do not use intermediate targets (local MPPs) – **directly model global MPP**

- Train **2 regressors** (can do in parallel, since independent):

$$[G, T, s, n_{sh}] \rightarrow P_{max}$$
$$[G, T, s, n_{sh}] \rightarrow V_{P_{max}}$$

- Given a reasonable amount of data **already beats closed-form equations**… But **can do better**!

Model 2: Stagewise modelling of global MPP

- First model local MPPs (intermediate targets), then predict global MPP

- Train **4 regressors** (can do in parallel, since independent):

$$\left.\begin{array}{l}[G, T, s, n_{sh}] \rightarrow P_1 \\ [G, T, s, n_{sh}] \rightarrow V_1\end{array}\right\} \text{MPP1}$$

$$\left.\begin{array}{l}[G, T, s, n_{sh}] \rightarrow P_2 \\ [G, T, s, n_{sh}] \rightarrow V_2\end{array}\right\} \text{MPP2}$$

- To predict global MPP: $\begin{cases} P_{max} = max\{P_1, P_2\} \\ V_{P_{max}} = \{V_{i^*} : i^* = \arg\max_{i \in \{1,2\}} P_i\} \end{cases}$

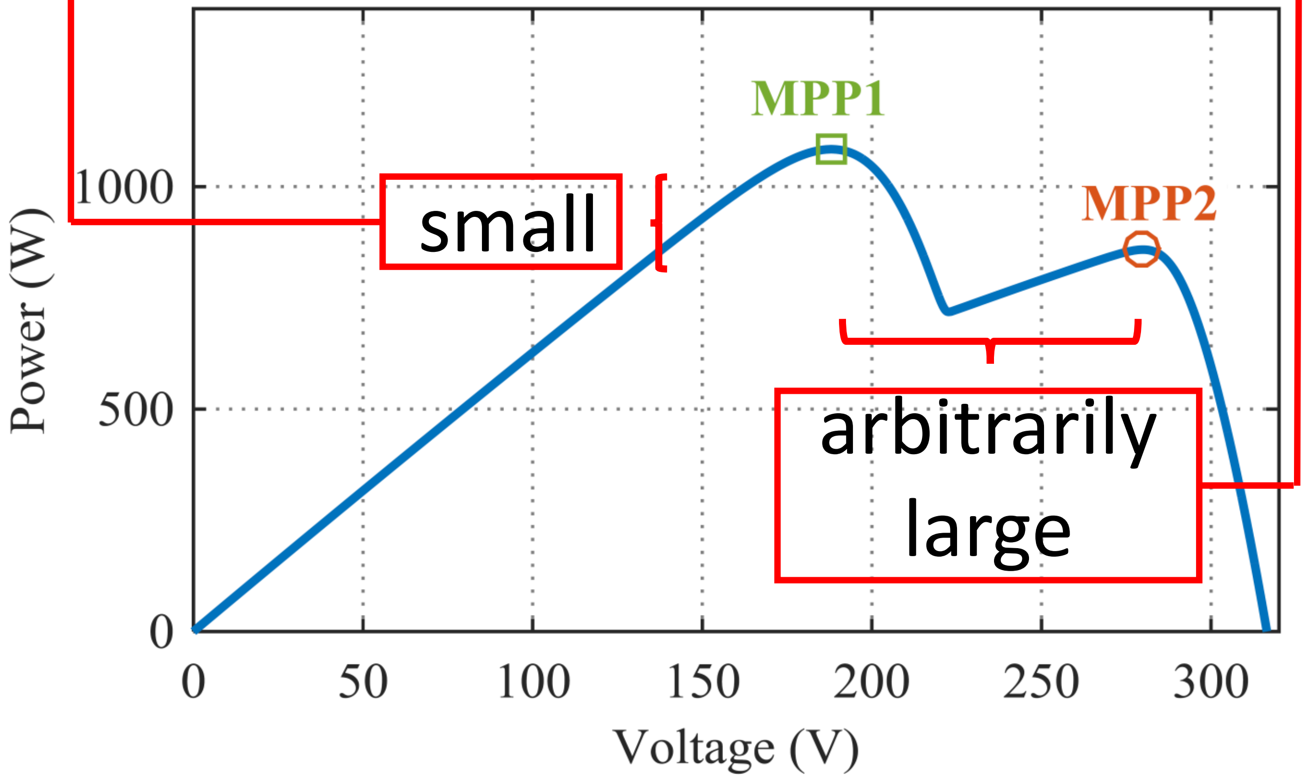
Model 2: Stagewise modelling of global MPP

- Given a reasonable amount of data **already beats closed-form equations**…
  Also **beats direct model** (Model 1)…
  But **can do even better**!

- **Why?** Because **intermediate outputs are FAR better estimated than those of closed-form equations**. In P_{max} this is reflected, but **why not** in $V_{P_{max}}$?

Model 2: Stagewise modelling of global MPP

- **Hypothesis**: In situations when $P_1 \cong P_2$, small estimation errors will have a small effect on P_{max}, but can cause us to predict the wrong V_i as $V_{P_{max}}$



- But $|V_1 - V_2|$ can be arbitrarily large, this can mean a large estimation error in $V_{P_{max}}$

$$\begin{cases} P_{max} = max\{P_1, P_2\} \\ V_{P_{max}} = \{V_{i^*} : i^* = \arg\max_{i \in \{1,2\}} P_i\} \end{cases}$$

Model 3: Stagewise, classifier-aided modelling of global MPP

- First model local MPPs (intermediate targets) & a mapping from input to the local MPP that is the global one, then predict global MPP

- Train **4 regressors & 1 classifier** (can do in parallel, since independent):

$$\left.\begin{array}{l}[G, T, s, n_{sh}] \rightarrow P_1 \\ [G, T, s, n_{sh}] \rightarrow V_1\end{array}\right\} \text{MPP1}$$

$$\left.\begin{array}{l}[G, T, s, n_{sh}] \rightarrow P_2 \\ [G, T, s, n_{sh}] \rightarrow V_2\end{array}\right\} \text{MPP2}$$

$$[G, T, s, n_{sh}] \rightarrow \{MPP1\ is\ global, MPP2\ is\ global\}$$

- To predict global MPP: If $MPP1\ is\ global$, then $P_{max} = P_1$ and $V_{P_{max}} = V_1$

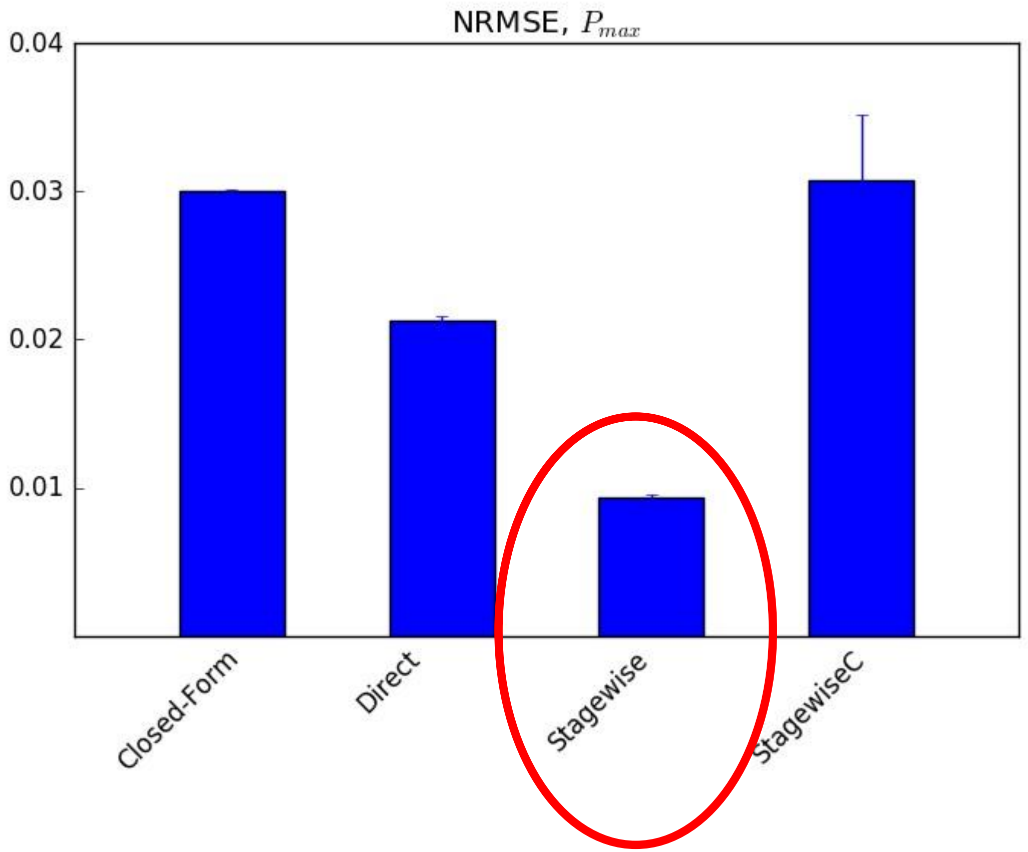
  Else $P_{max} = P_2$ and $V_{P_{max}} = V_2$

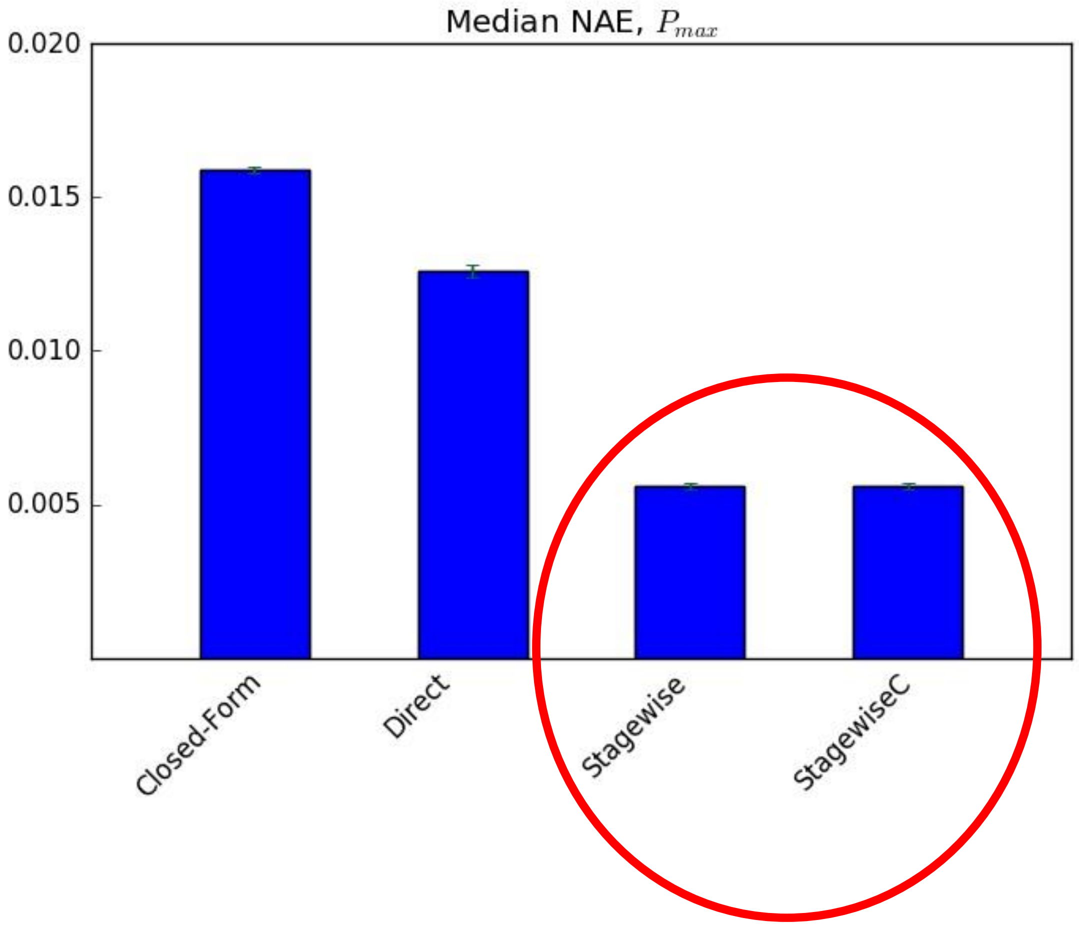
Experimental Setup

- 94905 datapoints generated by simulating circuit under various conditions
- Compare approximation of three models against closed-form estimates
- Ensemble size M=1000, tree depth d=3
- Trained on 75% of the data - have learning curves with fewer as well

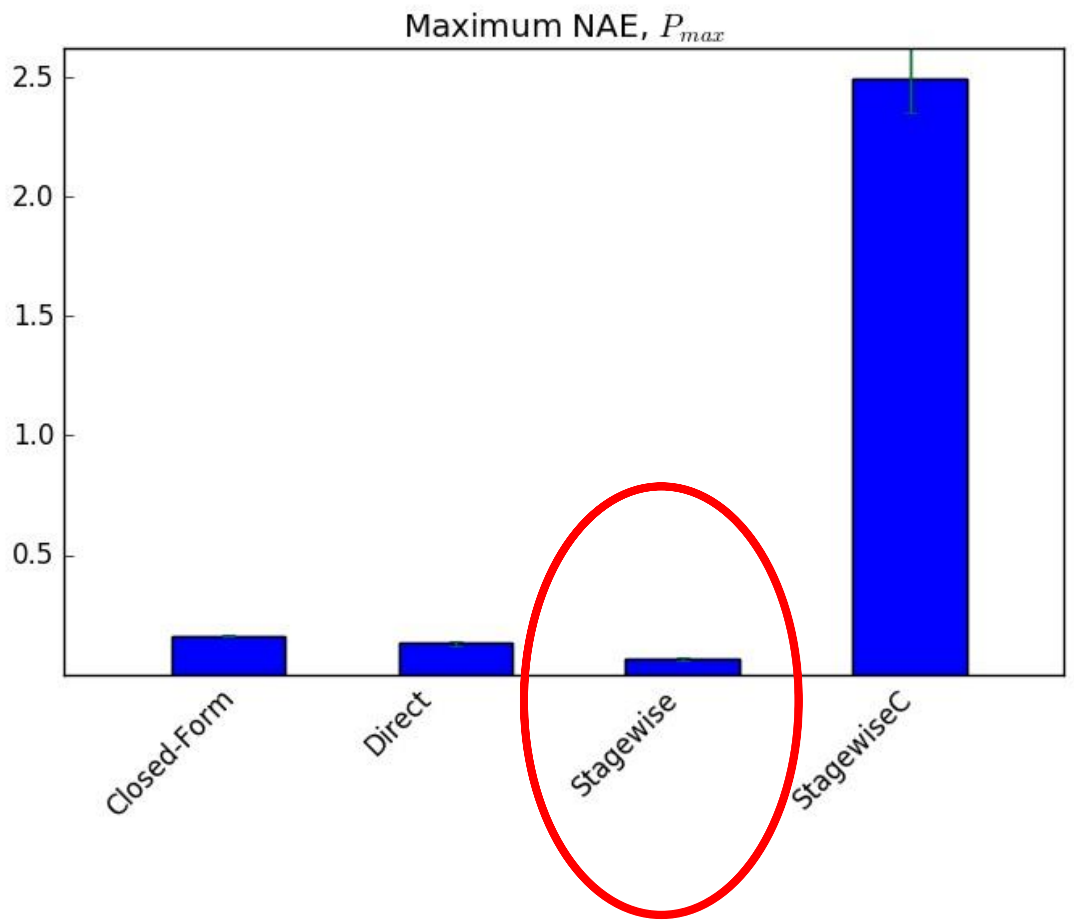
$$NRMSE = \sqrt{\sum_n (X_n - \hat{X}_n)^2} \Big/ \mu_X \qquad NAE_n = |X_n - \hat{X}_n| / \mu_X$$

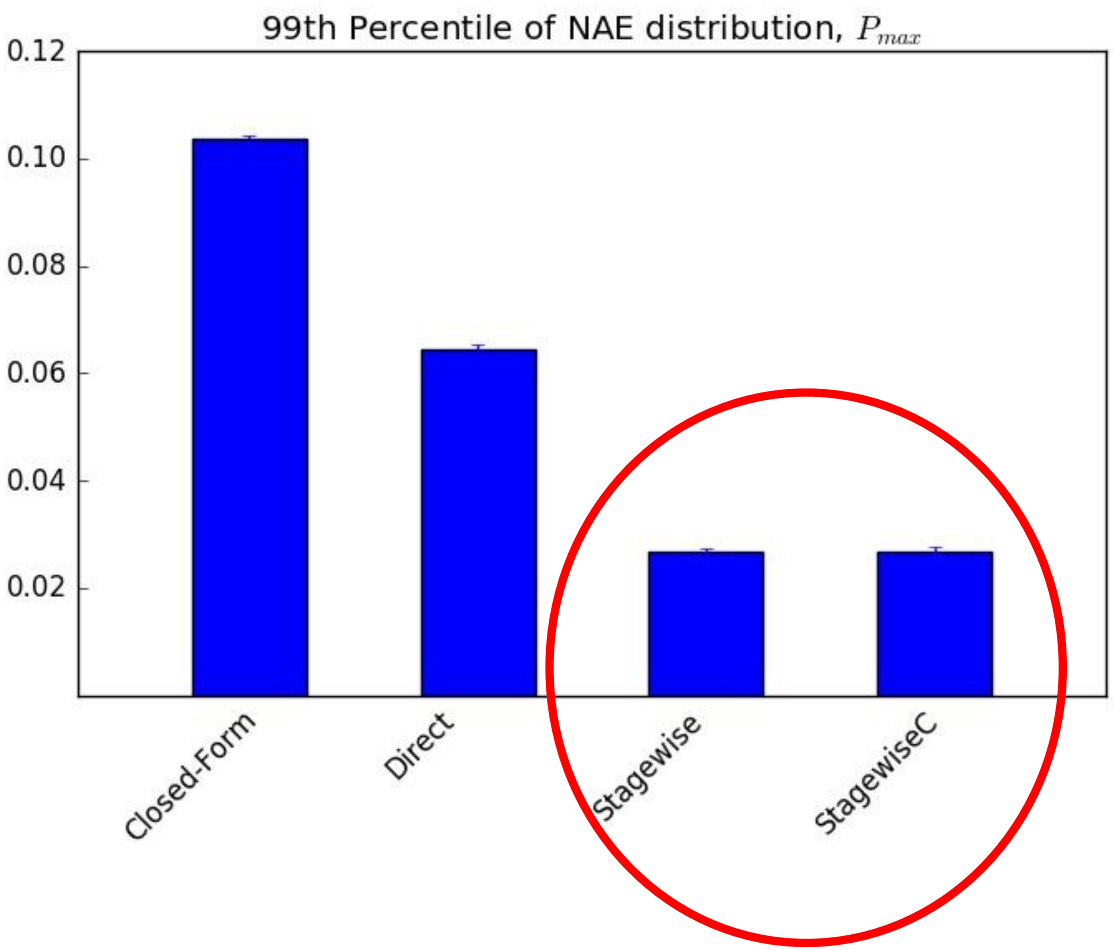
Results - P_{max} (Average NRMSE, Median NAE)



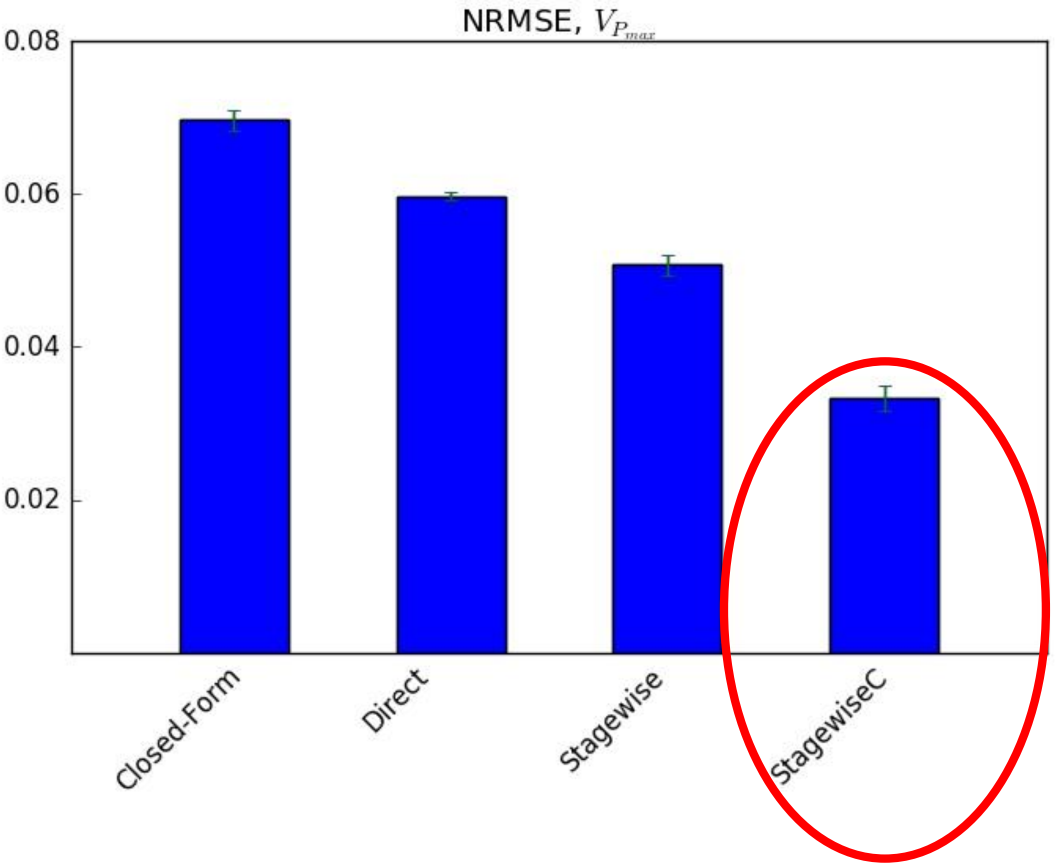


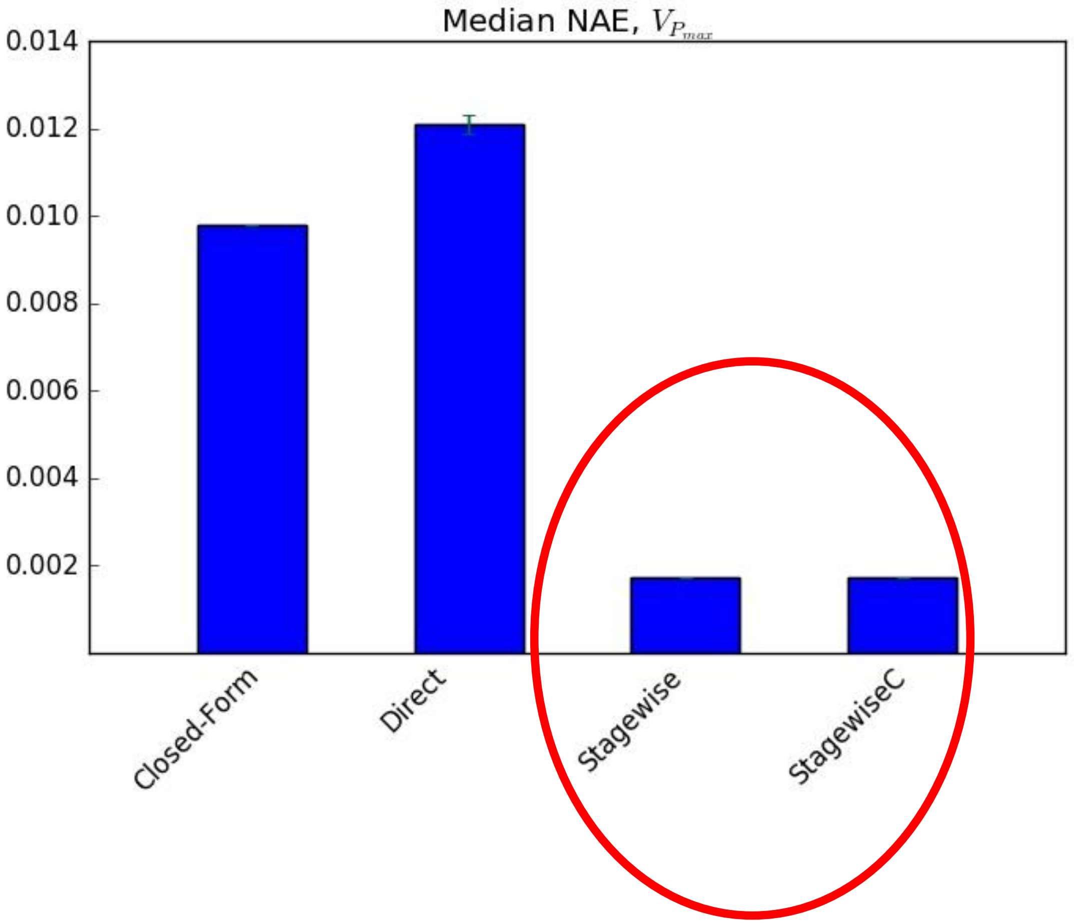
Results - P_{max} (Maximum NAE, 99th Percentile of NAE)



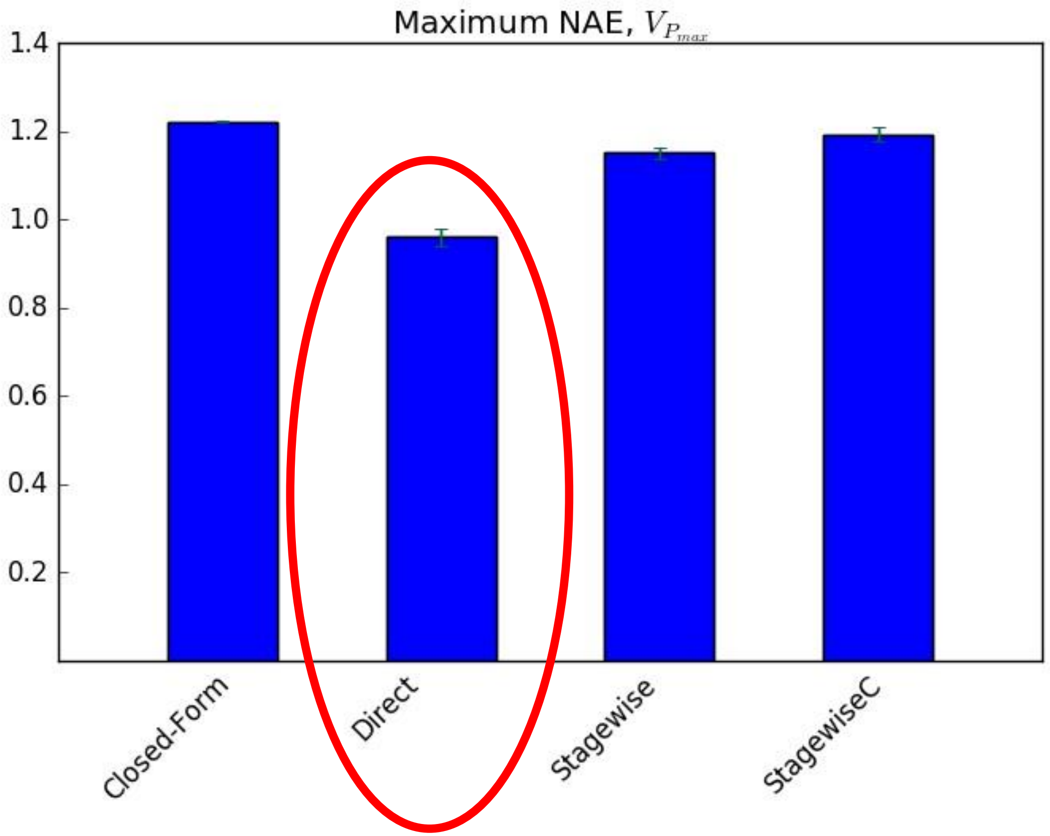


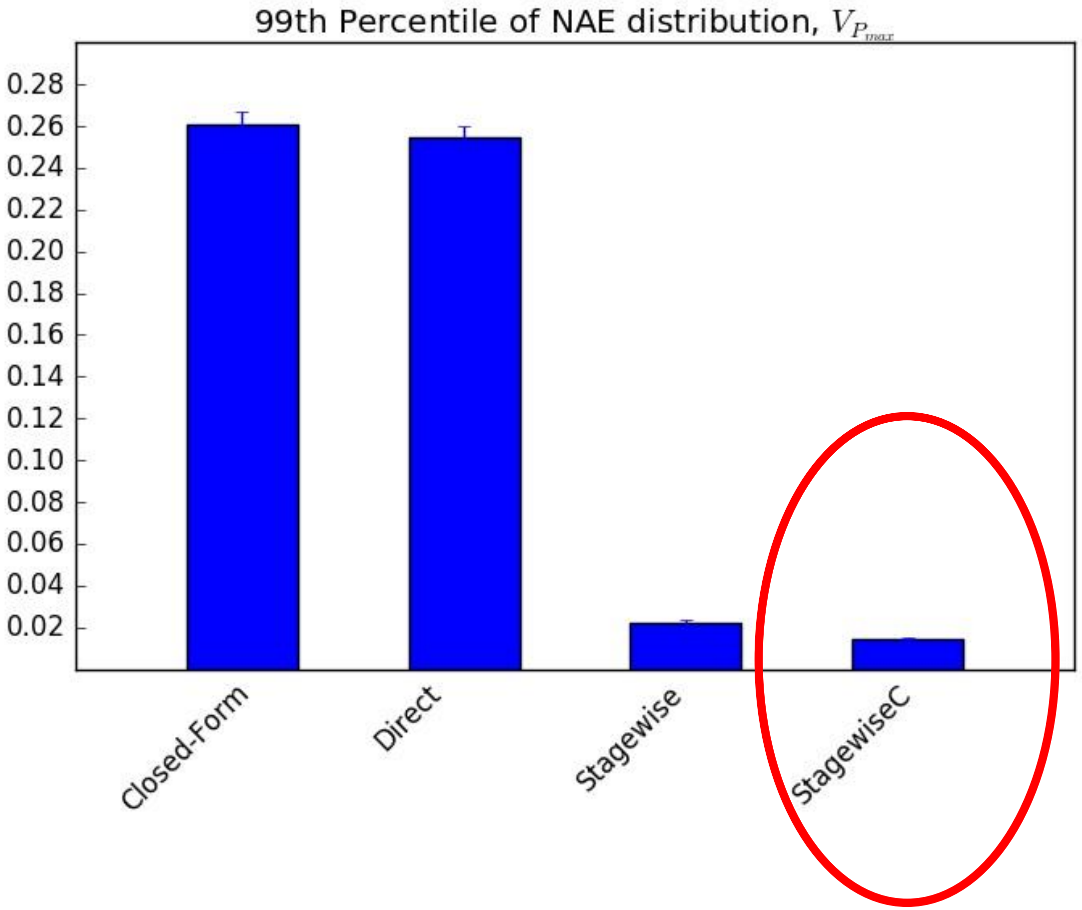
Results - $V_{P_{max}}$ (Average NRMSE, Median NAE)





Results - $V_{P_{max}}$ (Maximum NAE, 99th Percentile of NAE)

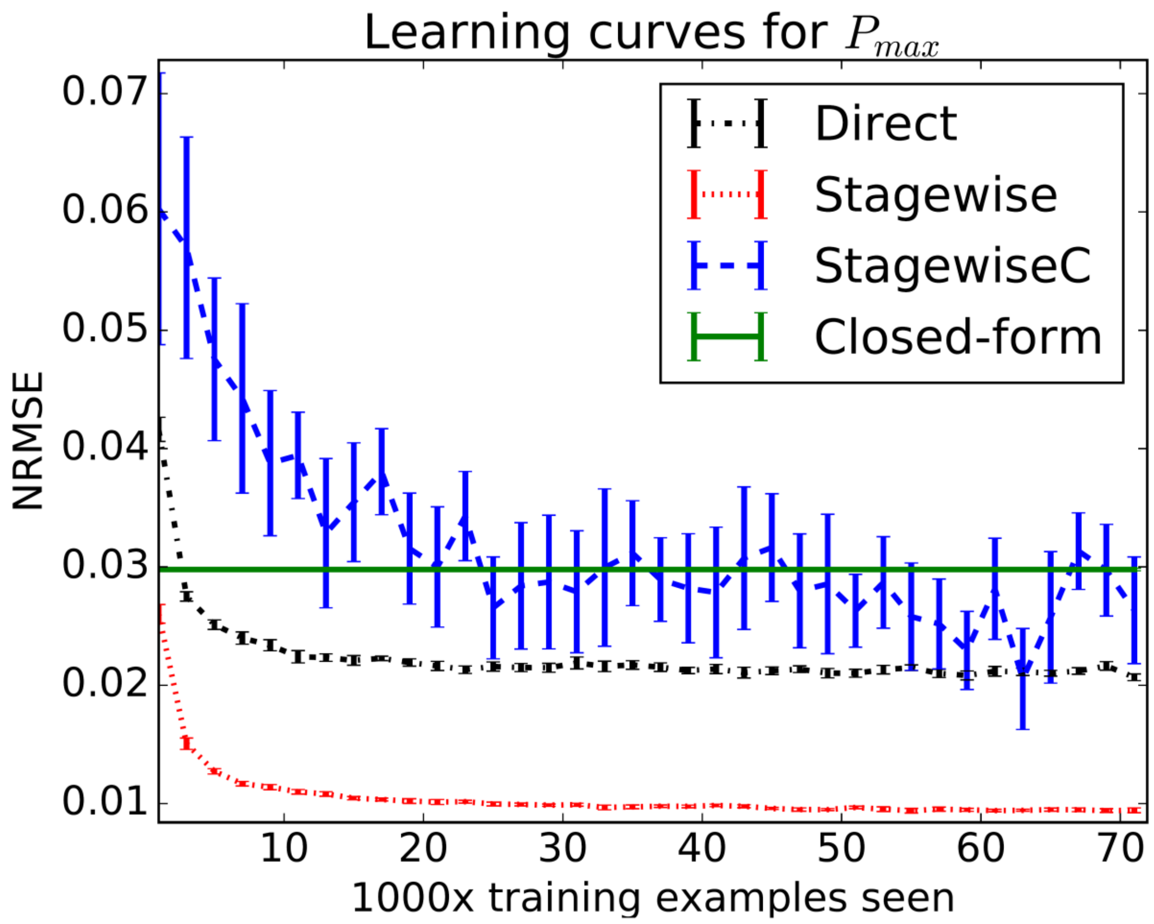


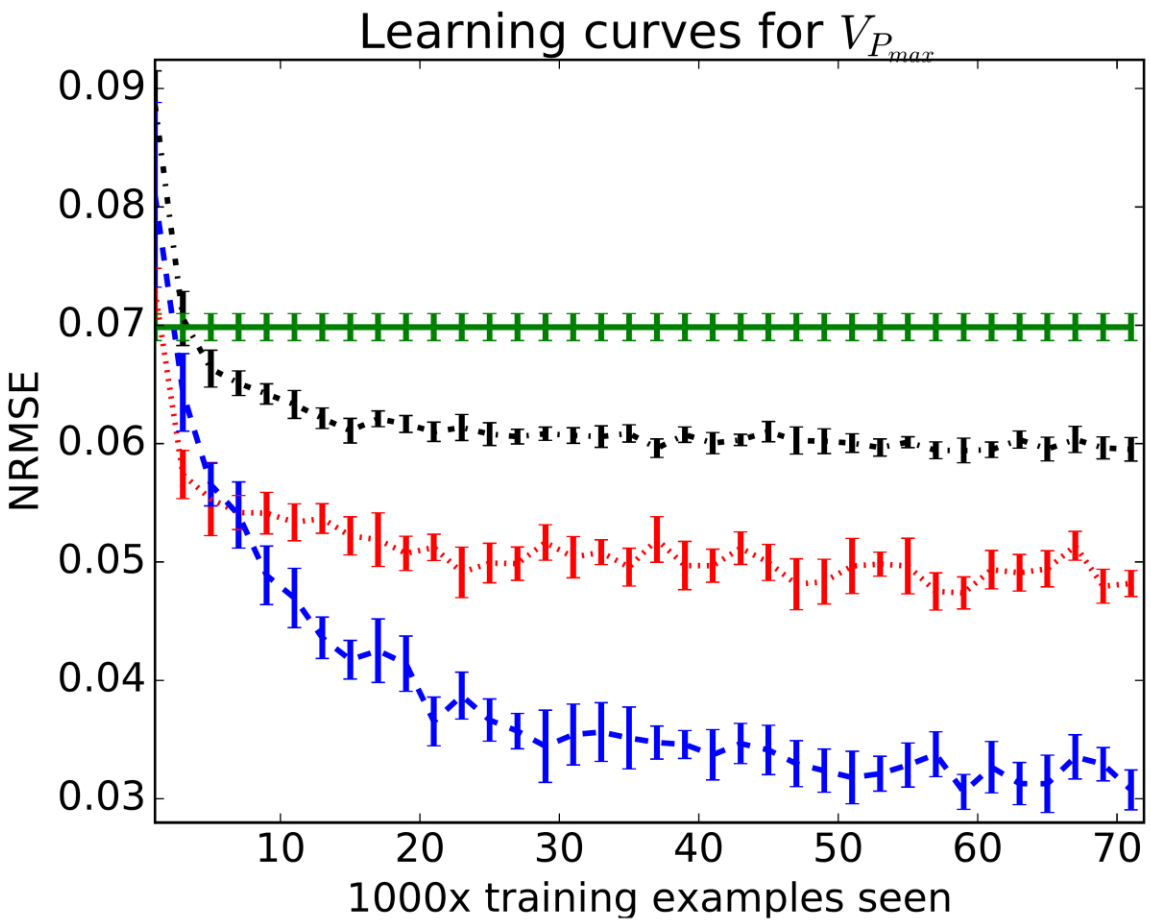


Results – advice for practitioners

- To minimize **maximum error in** $V_{P_{max}}$, use Model 1
- To minimize **average or maximum error in** P_{max} , use Model 2
- To minimize **average error in** $V_{P_{max}}$, use Model 3
- For **overall good** performance, use Model 2, or **combine** Models 2 & 3

Effect of training set size





Conclusions

- A **small training set is sufficient** to outperform closed-form…
- … **on average** (& median) **AND worst case**
- **Thin-tailed error distribution** - some statistical guarantees
- Increasing **ensemble size and/or tree depth** improves performance at increased computational cost
- To some degree **parallelizable**, **fast** to train - very fast to predict

Extensions

- More **irradiance levels** - up to 4-5 in practice
- Non-uniform **temperature**
- Different PV **configurations** **-** e.g. arrays (strings in parallel)
- More **machine learning methods** (Random Forests, Bagging, NNs)
- More experimentation with **hyperparameters,** multi-objective **optimization of cost & performance**
- Taking **correlations** into account
- **Interpreting models** - could relate them back to circuit theory

Thank you!