



RESEARCH BRIEF

A Machine Learning Approach to Evaluating Renewable Energy Technology: An Alternative LACE Study on Solar Photo-Voltaic (PV)

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Renewable generating technologies in the electricity market are often evaluated using the Levelized cost of electricity (LCOE), which is a measure of building and operating a generating plant over an assumed financial life and duty cycle. Using a more holistic approach, we measure the Levelized Avoided Cost of Electricity (LACE), which considers what it will cost the grid to generate electricity using renewable technology, amortized over its lifetime, to assess the economical value of the renewable generating technology. We explore several methods of evaluating alternative sources of energy, with an in-depth focus on a LACE evaluation of solar PV as an alternative source of electricity generation within California Independent System Operator (CAISO) market. Through experimentation of different variants of a recurrent neural network, a Long Short-Term Memory (LSTM) model was trained to predict 2016 electricity prices of all nodes within CAISO. We found that the smaller the difference in the estimated LACE to the respective LCOE value, the greater the impact of improving price prediction performance; and was able to place an implicit value of an improvement of price prediction performance. Especially for policy and decision makers, this improvement in electricity price forecasting would directly translate to greater confidence when making the decision to switch a solar PV alternative.

Within the US electricity market, renewable technologies are often evaluated using the Levelized cost of electricity (LCOE), which is a measure of building and operating a generating plant over an assumed financial life and duty cycle. Naturally, instead of only measuring the cost, a more holistic

approach would be to also assess the economical value of the renewable generating technology. In this research, we will use the Levelized Avoided Cost of Electricity (LACE), which considers what it will economic benefits it brings the grid to generate electricity, amortized over its lifetime, to understand the following: 1) can we better leverage on Machine Learning and Optimization techniques to achieve better estimates of the value of solar technology; 2) based on these estimates, how does this compare against traditional cost estimates of alternative energy; 3) can we place an implicit value on an improvement of price prediction, especially in the context of making better decisions during policy considerations.

To address these questions, we will implement current state of the art machine learning techniques to forecast 2016 electricity prices within the CAISO electricity market. Specifically, we will be experimenting with different variants of a recurrent neural network (RNN), which includes starting with an basic RNN, and then adding Gated Recurrent Units (GRU) and Long Short-Term Memory (LSTM) units to train a model that will return the best prediction accuracy. Part of creating this model will also involve carrying out hyperparameter tuning, using a basic grid search algorithm, to compare among different model architectures and select a final model architecture that is customized to the CAISO market and has the best prediction power. These predicted prices will be incorporated with meteorological data, such as solar radiation values, in the respective nodal locations to determine the LACE of solar technology across all the various nodes in the CAISO market.

We continue to investigate on the effects of improving the prediction power of electricity prices and its impact on respective LACE values. This will be done through understanding underlying characteristics of the prediction errors from our machine learning model. Subsequently, we will simulate new prediction errors with various scale and analyze the respective LACE

values determined.

From a policy and decision making perspective, the LCOE is currently still the leading measure when it comes to evaluating alternative sources of electricity generation. We will relate this to the LACE of respective nodes calculated and identify a breakeven cost to determine when and how decision makers can evaluate benefits of switching to solar alternatives. Finally, linking back to a machine learning view, we will estimate an implicit value to the benefits that an improvement of prediction performance of machine learning can bring to decision makers.

Overall, a LSTM model was found to be the best model to predict hourly CAISO electricity prices with an Mean Absolute Scaled Error (MASE) of 0.761, indicating that the prediction performance outperforms a naïve baseline of using the DA price of the same hour. An indepth analysis of the prediction errors found that they follow a normal distribution and this relationship was used to simulate 2000 'predictions' to compare the expected LACE to the respective simulated Mean Absolute Percentage Error (MAPE) rate. Figure 1 below shows an example of simulated LACE versus MAPE with the blue line indicating the expected LACE. The breakeven point is determined when you incorporated the estimated LCOE (red line) of solar at the node, with a LACE valuation above the LCOE presenting a strong case for a switch to alternative sources of electricity generation. With reduced variability of our LACE valuation, the greater confidence of being above the breakeven point (figure 1). This represents an approximate change of 1% decrease in confidence for every % increase in MAPE. Our prediction model currently reports a MAPE of about 0.25. Based on current LCOE values from EIA Annual Report 2020, when we this compare with the LACE computed from our model, only less than 0.5% of nodes in CAISO would break even at today's LCOE for solar PV.

About the Center for Energy and Environmental Policy Research (CEEPR)

Since 1977, CEEPR has been a focal point for research on energy and environmental policy at MIT. CEEPR promotes rigorous, objective research for improved decision making in government and the private sector, and secures the relevance of its work through close cooperation with industry partners from around the globe. CEEPR is jointly sponsored at MIT by the MIT Energy Initiative (MITEI), the Department of Economics, and the Sloan School of Management.

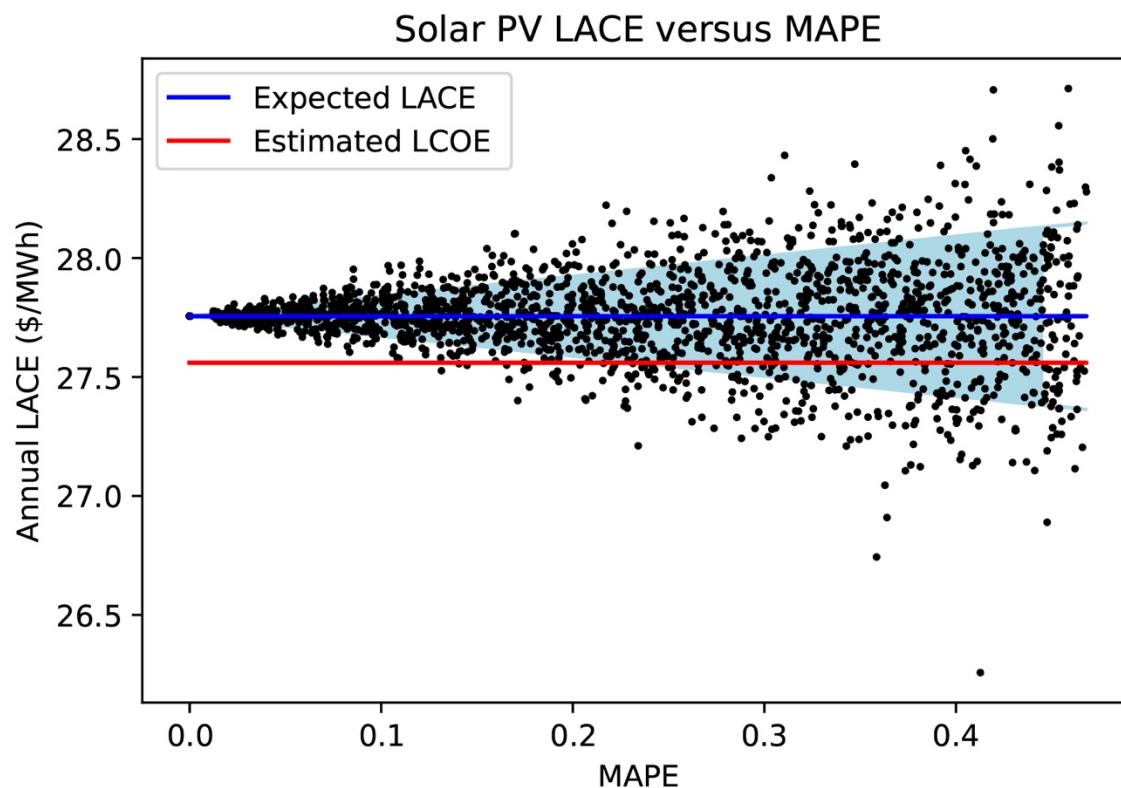


Figure: Plot of simulated LACE versus Mean Absolute Percentage Error ($n = 2000$) for an example node in CAISO. The blue line indicates the expected LACE based on 2016 predicted prices, the red line indicates the estimated LCOE, and the light blue area denotes the standard deviation of the simulated LACE computation.

References

Benny Siu Hon Ng, Christopher R. Knittel, and Caroline Uhler (2020) "A Machine Learning Approach to Evaluating Renewable Energy Technology: An Alternative LACE Study on Solar Photo-Voltaic (PV)", MIT CEEPR Working Paper 2020-021.

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About the Authors



Benny Ng was a Research Assistant for Professor Christopher Knittel at CEEPR focused on research in U.S. electricity markets as well as workforce development in the climate change sector. He recently earned her M.S in Technology and Policy Program and M.S in Electrical Engineering and Computer Science at MIT. Benny has previous experience as a Technology consultant at Accenture, and is now a Data Scientist for Microsoft in Boston, MA.



Christopher R. Knittel is the George P. Shultz Professor of Applied Economics at the Sloan School of Management, Director of the Center for Energy and Environmental Policy Research, and Co-Director of the MITEI Low-Carbon Energy Center for Electric Power Systems Research at the Massachusetts Institute of Technology. He joined the faculty at MIT in 2011, having taught previously at UC Davis and Boston University. Professor Knittel received his B.A. in economics and political science from the California State University, Stanislaus in 1994 (summa cum laude), an M.A. in economics from UC Davis in 1996, and a Ph.D. in economics from UC Berkeley in 1999. His research focuses on environmental economics, industrial organization, and applied econometrics.



Caroline Uhler joined the MIT faculty in 2015 and is currently the Henry L. and Grace Doherty associate professor in EECS (Electrical Engineering & Computer Science) and IDSS (Institute for Data, Systems and Society). She is a member of LIDS (Laboratory for Information and Decision Systems), the Center for Statistics, Machine Learning at MIT, and the ORC (Operations Research Center). She holds an MSc in mathematics, a BSc in biology, and an MEd in mathematics education from the University of Zurich, and a PhD in statistics from UC Berkeley. Before joining MIT, she spent a semester in the "Big Data" program at the Simons Institute at UC Berkeley, postdoctoral positions at the IMA and at ETH Zurich, and 3 years as an assistant professor at IST Austria. Her research focuses on statistics, machine learning and computational biology.

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