

Increasing the granularity of the CEC forecasting model: Some technical issues

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Synopsis

- There are valid reasons for increasing the granularity / degree-of-disaggregation of the CEC demand forecasting model
- However, it is important to recognize that meeting this goal
 - Entails costs as well as benefits
 - Is subject to limitations on what is likely to be achieved in terms of model performance improvements

Data issues

- As granularity increases, so do data demands
- Obtaining, or generating, high-quality data needed to parameterize the model at a substantially increased degree of spatial disaggregation is likely to be quite costly, and may be impossible
 - Using sparse, incomplete, or lower-quality data will tend to offset the gains from increased resolution

Accuracy at different levels

- In general, in part because of data issues, it is easier to accurately predict aggregate quantities than dis-aggregate
 - This phenomenon is true in many modeling applications, not just energy
- An example: Retrospective examination of US EPA energy model
 - 10-year *national* projection of electricity had error < 5%
 - But 10-year *regional* projection errors were up to 20%

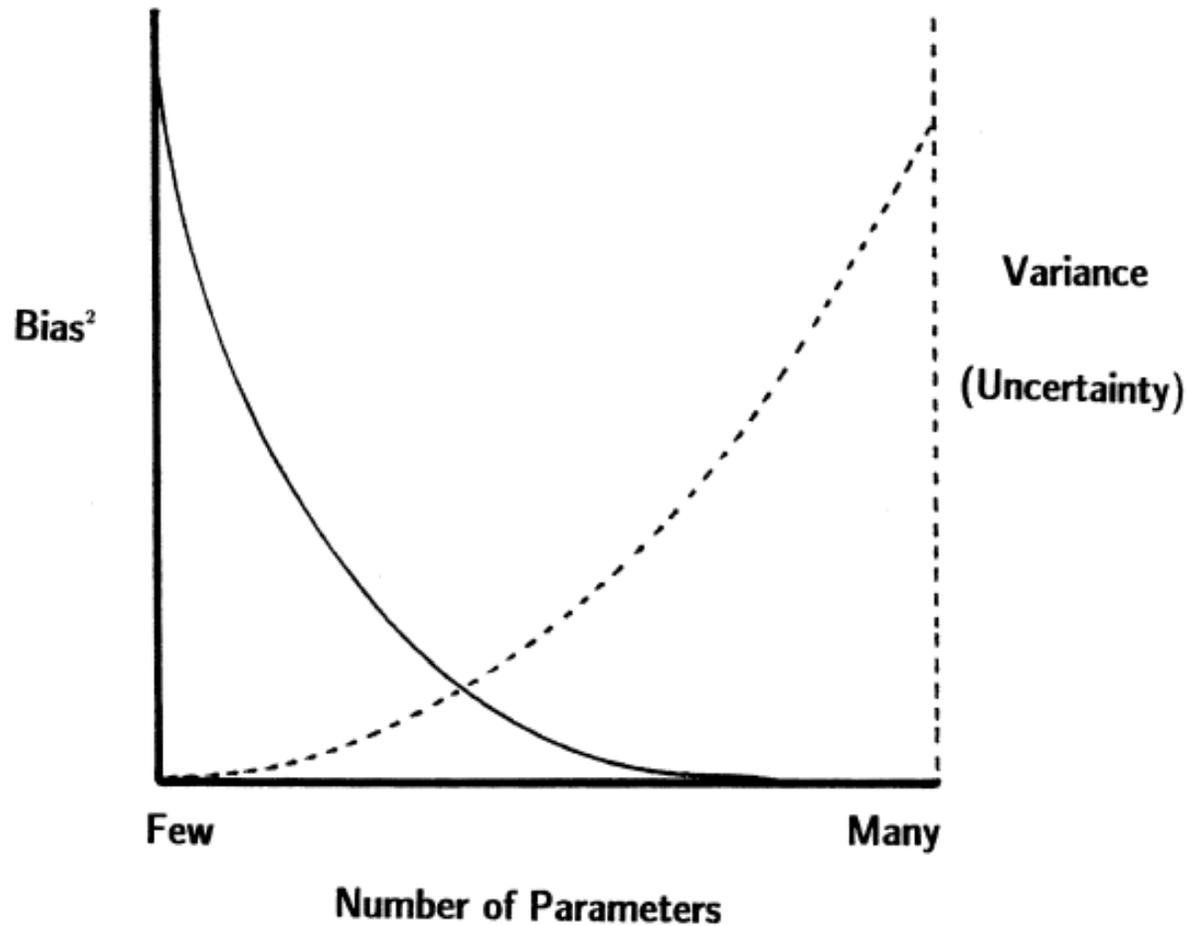
A fundamental constraint

- There are principles of model complexity, accuracy, and uncertainty that apply to the goal of developing a very high-resolution model
- In general, there is a trade-off between increasing model accuracy and decreasing model uncertainty as complexity increases
 - This is known as the “**bias-variance trade-off**” in statistics and information theory

Bias-variance relationship

- Estimating – e.g., forecasting – a quantity Y with a model $F(X)$
- Mean-squared error of estimator: $E(Y - F(X))^2$
 - “ E ” is expected value
- Bias-squared: $(Y - E(F(X)))^2$
- Variance: $E(F(X) - E(F(X)))^2$
- Fundamental relationship:
$$MSE = Bias^2 + Variance$$

Model complexity and the bias-variance trade-off



Discussion

- It is also important to recognize that the decrease in bias illustrated here implicitly refers to results *on average* in a statistical sense
- This would apply when a large number of model solutions – e.g., projections – can be generated
- However, when only a relatively small number of projections or scenarios are computed, one is essentially sampling once, or a few times, from a distribution with increasing variance
 - The “uncertainty effect” will dominate
- Thus, in non-statistical models, increased complexity may increase uncertainty without improving accuracy

Concerns

- When a model is used purely to create scenarios that may yield insight into policy issues, this issue may not be as important
- However, when forecast accuracy is a concern, it may have significant implications
 - In the present case, use of CEC forecasts by CAISO and other entities is for actual planning
 - Both accuracy and uncertainty are critical considerations

Possible implications

- Example: Forecasting that has traditionally been disaggregated to the utility service territory level is taken down to the census tract level.
- Depending upon how this is done:
 - The accuracy of the aggregate and utility-level forecasts might be maintained, but census-tract level accuracy could be poor
 - The aggregate forecast might lose accuracy if the entire model is re-calibrated from the census tract level up

Recommendations

- Carry out a thorough assessment of data availability and quality **before** introducing a significant increase in granularity of the model
 - The dis-aggregation should be determined in part by data issues specifically
- Carefully analyze the implications for planning of high potentially high uncertainty in newly detailed forecasts
 - Among other questions: How would planning authorities – e.g., CAISO – hedge against possible risks introduced by this uncertainty?

- The Expert Panel looks forward to engaging in discussions of and work on these issues

Thank you

The opinions presented here are solely those of the speaker and do not reflect views of the Lawrence Berkeley National Laboratory, the University of California, or the U. S. Department of Energy

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