Assessing the Accuracy of Electricity Production Forecasts in Developing Countries

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Why Accurate Forecasting of Electricity Production is Important?

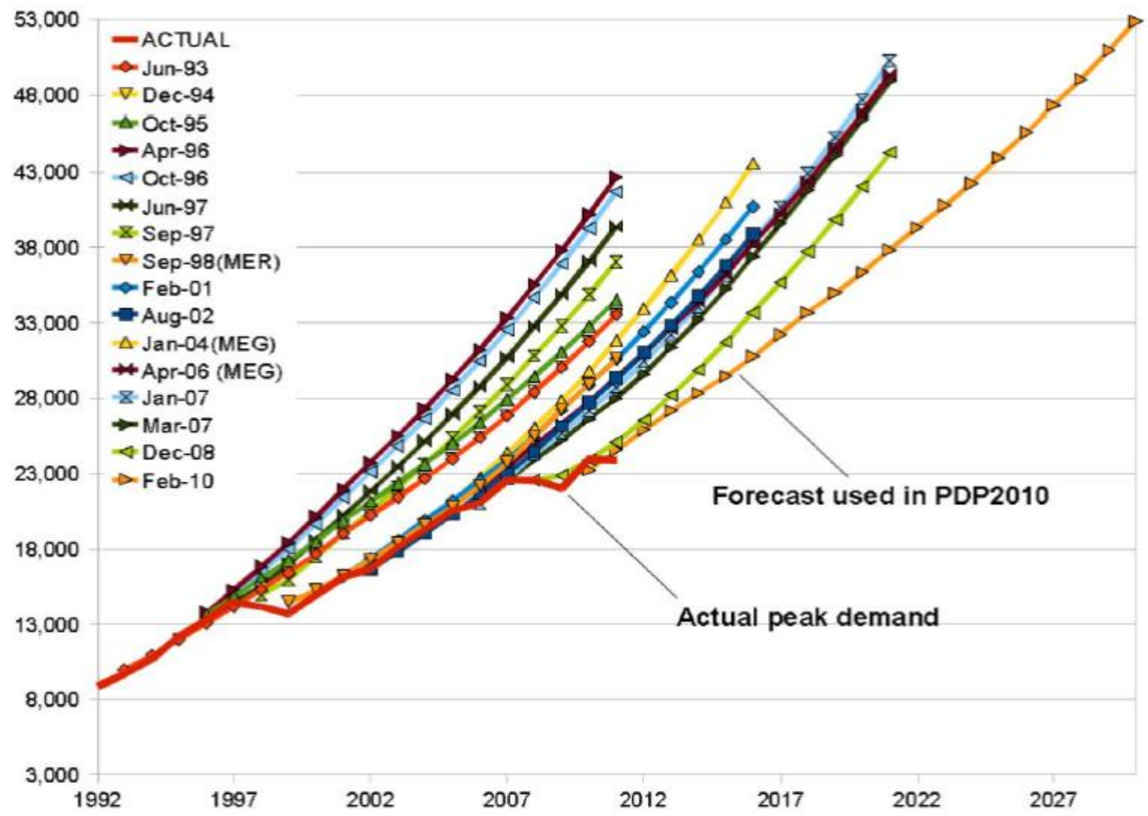
- Strong correlate of electricity demand
  - The only reliable information in many developing countries
  - Almost perfect correlate in the absence of suppressed demand / trade
- Reliable forecasts are essential for
  - short-term load allocation and
  - long-term planning for future generation and transmission
- Poor quality forecasts result in
  - supply shortages and forced power outages (downward-biased forecasts)
  - over investment in generation and stranded assets (upward-biased forecasts)
  - higher electricity prices
  - slower economic growth
- This study focuses on Long-Term Demand Projections

Recent Examples from Developing Countries Illustrate the Scope of the Problem

- Sri Lanka: downward-biased forecast; underinvestment in generation capacity; decades of endemic power shortages in the years 1990-2007;
- Indonesia: 2014-2015, power tariffs doubled; demand growth in 2015 was 30% less than expected;
- Malaysia: Incorrect anticipation of high electricity demand led to overinvestment in coal production capacity, with resulting production reserve margin of 60%.
- India: ambitious investment of 100GW solar capacity; some concerns of overly optimistic electricity demand projections
- Brazil and Nepal: massive investments in (costly) hydropower; demand forecasts are not very reliable

Thailand: A Lower Envelope of Demand Forecasts

Figure 68 **Thailand Power Development Plan Forecasts and Actual Demand**[8]



Source: Chuenchom Sangarasri Greacen and Chris Greacen (2012), "Proposed Power Development Plan (PDP) 2012 and a Framework for Improving Accountability and Performance of Power Sector Planning"

Vietnam: Forecasts Errors are Growing

Table 10 Comparison between PDP 7 Forecasted and Actual Electricity Demand (2011-14)

Year	Energy (GWh)				Pmax (MW)			
	PDP 7	Actual	Disparity		PDP 7	Actual	Disparity	
			GWh	%			MW	%
2010	86,756	86,756	0	0.0%	15,416	15,416	0	0.0%
2011	100,727	94,658	6,069	6.0%	18,405	16,490	1,915	10.4%
2012	115,332	105,474	9,858	8.5%	21,035	18,603	2,432	11.6%
2013	131,594	115,069	16,525	12.6%	23,957	20,010	3,947	16.5%
2014*	149,622	126,500	23,122	15.5%	27,189	22,176	5,013	18.4%

Source: Intelligent Energy Systems (2015)

Why Electricity Production/Demand is So Difficult to Forecast?

- Methodological and Data Issues
  - Variety of forecasting methods / models
    - Econometric Time-Series Models
    - Computational Economic Models (CGEs / DSGEs / DCGEs)
    - Bottom Up PE End Use Models (e.g., TIMES/MARKAL, LEAP)
    - Algorithmic / Generic models (ANNs)
  - Difficult to sort out between appropriateness of each approach; no clear benchmarking was ever done!
  - Computational models take time and are costly to develop and maintain
  - Econometric models are highly sensitive to data availability
- Political pressures to generate overly optimistic forecasts

Practitioners frequently reply on simple heuristics not models

- An example of ‘typical’ forecasting approach:

$$d = g * a - p * b,$$

where

d = forecast of annual rate of demand growth
g = forecast of real income or GDP growth
a = income elasticity of electricity demand
b = price elasticity of electricity demand
p = forecast of real power prices (tariffs)

- Some rules are even more simple:
  - Electricity demand grows at predetermined (historical) rate
  - Electricity demand is proportional to GDP as 1:1.

What is wrong with relying on simple rules?

- Require estimates of electricity tariffs and GDP growth rates
  - In many developing countries regulators don’t have clear methodologies for setting tariffs, those are set up on completely ad hoc basis
  - GDP forecasts themselves are noisy
- Require estimates of electricity demand price and income elasticities
  - These estimates are typically pure guess
  - Income elasticity of electricity demand varies with income levels (non-homotheticity of electricity demand)
- Miss other important drivers of electricity demand

Objectives of this Study

- Develop a econometric framework for forecasting electricity production;
- Evaluate accuracy of the electricity production forecasts resulting from different econometric methods and model specifications
- Provide off-the-shelf forward-looking 10 year production forecasts for 106 developing countries

Methodology

- Step 1: Test for Data Stationarity
  - Forecast variance increases linearly with forecast horizon; approaches infinity for non-stationary time series (Hendry and Clements 2001)
  - Modified Dickey-Fuller *t* test (Elliott et al 1996)
- Step 2: Employ a portfolio of forecasting methods to obtain a number of competing forecasts
  - within sample forecasts over 5 and 10 year horizon
  - see next slide for method descriptions
- Step 3: Calculate Forecast Accuracy Measures
  - Absolute accuracy methods (is method accurate?)
  - Relative accuracy methods (how does method fare against other methods?)

Time-Series Models

- VAR / VEC– multivariate autoregression / error-correction models
  - employs multiple determinants of electricity production, which are co-determined
- ARIMA / GARCH – univariate time-series models
  - Electricity production mean and variance is decomposed into autoregressive and moving average components
  - Non-stationary data are differenced until unit roots are eliminated
- Holt-Winters / UCM – estimate electricity production trend
  - can be deterministic or stochastic (random walk, RW).
  - UCM-RWSC also includes a stochastic cycle component
- Average of the forecasting models above

Accuracy Measures

- $sMAPE = \frac{1}{T}\sum_{i=1}^{T}\left[\frac{|y_t^F - y_t|}{(|y_t^F| + |y_t|)/2}\right]$
  - symmetric, bounded, percentage error measure
- $RMSE = \sqrt{\frac{\sum_{i=1}^{T}(y_t^F - y_t)^2}{T}}$
  - forecast outliers are particularly undesirable
- $MdRAE = p_{50}\left\{\frac{|y_t^{F,i} - y_t|}{|y_t^{F,Naive} - y_t|}\right\}$
  - evaluates model performance relative to three benchmarks:
    - pure random walk
    - electricity production proportional to GDP growth
    - AR(1) model
  - Diebold and Mariano (1995) test assesses whether differences between competing forecasts are statistically significant

Data

- The electricity production (net generation)
  - OECD/IEA Extended World Energy Balances
- Real GDP and Population
  - Penn World Tables (version 9)
- Exogenous shocks affecting production
  - Wars / Insurgencies (Uppsala U database)
  - Major natural disasters (Munich RE database)
- 106 developing countries
  - Include very recent OECD members and Turkey
- 52 years time series from 1960 to 2012
- Sorting by region, income category, system capacity, energy intensity, electrification rates, oil exports

More complex autoregressive models tend to perform better …

Frequency Tabulation of Best Performing Methods: sMAPE criterion

Model	5 year forecast horizon		10 year forecast horizon	
	Count	Frequency	Count	Frequency
VAR3 / VEC3	13	12.26%	21	20.00%
VAR2 / VEC2	20	18.87%	18	17.14%
GARCH	43	40.57%	44	41.90%
ARIMA	14	13.21%	11	10.48%
HOLT-WINTERS	5	4.72%	7	6.67%
UCM	10	9.43%	2	1.90%
AVERAGE	1	0.94%	2	1.90%
Total	106	100%	105	100%

… outperforming random walk …

Model	5 year forecast horizon		10 year forecast horizon	
	Median	% significant	Median	% significant
	% Better	(p = 0.05)	% Better	(p = 0.05)
Lowest sMAPE	79%	79.57%	76%	66.67%
VAR3 / VEC3	10%	78.82%	5%	66.34%
VAR2 / VEC2	0.30%	77.88%	0.80%	57.69%
GARCH	36%	77.65%	23%	70.48%
ARIMA	15%	81.61%	-7%	71.43%
HOLT-WINTERS	0.50%	85.87%	-9%	80.95%
UCM-RWD	-10%	87.50%	-26%	85.42%
UCM-LLTM	-11%	89.61%	-27%	85.42%
UCM-RWC	-48%	96.88%	-58%	93.59%
Average	-22%	89.87%	-33%	69.52%

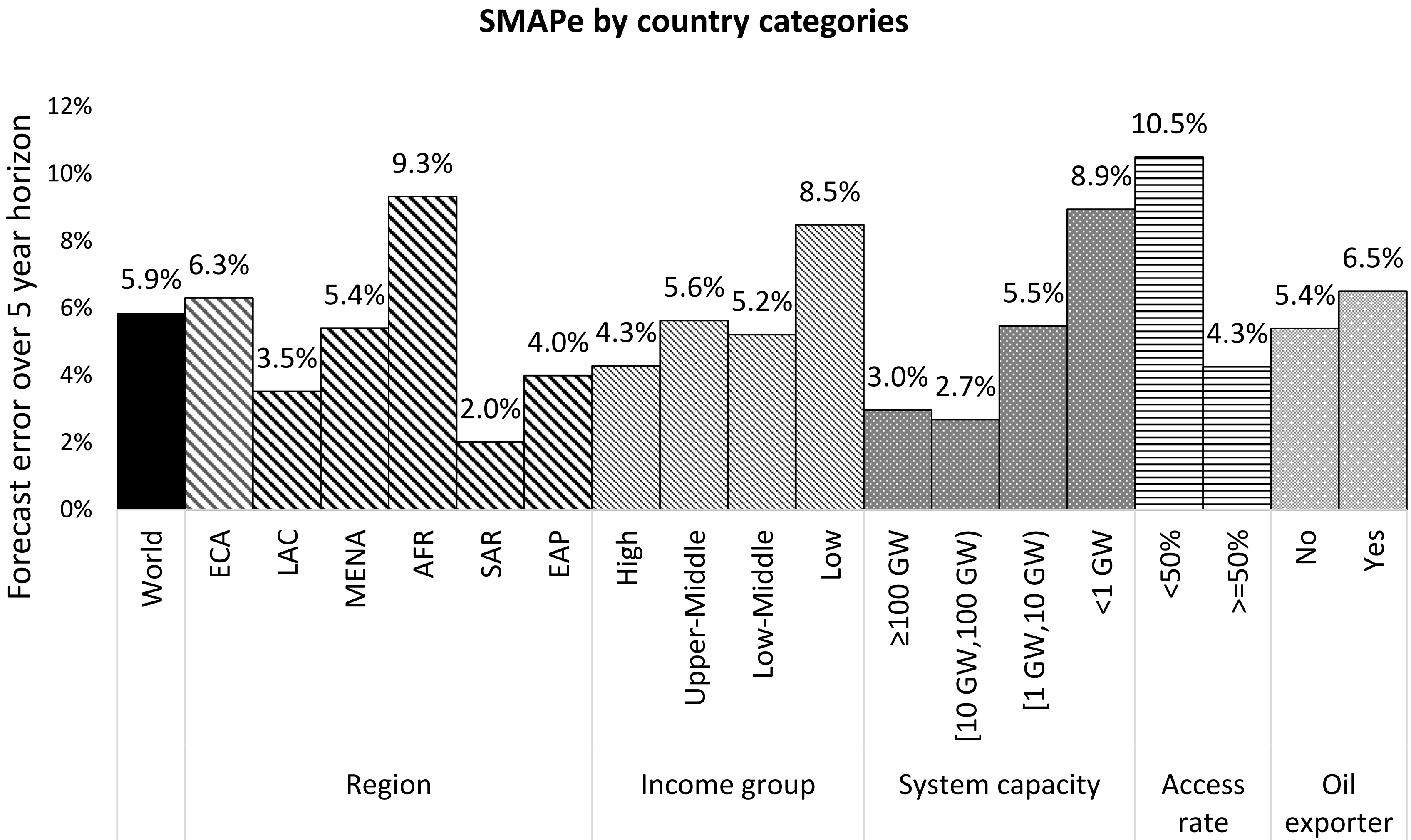
… being an order of magnitude more accurate than heuristic models…

Model	5 year forecast horizon		10 year forecast horizon	
	Median	% significant	Median	% significant
	% Better	(p = 0.05)	% Better	(p = 0.05)
Lowest sMAPE	202%	86.05%	101%	68.27%
VAR3 / VEC3	33%	90.28%	26%	68.32%
VAR2 / VEC2	20%	81.55%	16%	48.08%
GARCH	141%	88.10%	62%	70.19%
ARIMA	69%	84.62%	18%	75.00%
HOLT-WINTERS	43%	87.95%	12%	81.73%
UCM-RWD	31%	90.80%	-13%	83.16%
UCM-LLTM	21%	94.44%	-13%	81.05%
UCM-RWC	-37%	93.15%	-53%	90.91%
Average	-17%	90.00%	-31%	65.38%

… also selectively outperforming AR(1) …

Model	5 year forecast horizon		10 year forecast horizon	
	Median	% significant	Median	% significant
	% Better	(p = 0.05)	% Better	(p = 0.05)
Lowest sMAPE	87%	39.05%	117%	27.62%
VAR3 / VEC3	12%	82.35%	46%	68.32%
VAR2 / VEC2	1%	75.73%	17%	50.96%
GARCH	40%	13.21%	43%	6.67%
ARIMA	17%	6.80%	16%	1.92%
HOLT-WINTERS	5%	5.66%	12%	0.95%
UCM-RWD	-1.50%	6.60%	-0.70%	3.13%
UCM-LLTM	-2%	7.37%	-0.80%	1.04%
UCM-RWC	-47%	6.32%	-48%	0.00%
Average	-26%	5.13%	-15%	1.90%

… and having reasonable forecast errors



The quality of electricity demand forecasts diminishes for

- the countries of Sub-Saharan Africa region
- the low-income countries
- the countries with small electricity generation systems / low access

Key Takeaways

- Time-series econometric methods yield highly accurate forecast predictions
- These predictions are of an order of magnitude more accurate than those based on simple heuristics
- Simple and parsimonious econometric models are advised for practitioners when alternatives do not exist or costly to develop.

But Keep in Mind That

- Time-series econometric methods are not bullet proof:
  - Backward looking, extrapolate existing trends
  - Poorly applicable for cases when additions to / divestures of generation capacity are planned in the near future
  - Do not pick up well electricity trade (if significant)
  - Sensitive to unexpected events (disasters, conflicts, etc.)
- Alternative forecasting methods are strongly advised in these situations

THANK YOU!

- The results of the study are disseminated as
  - J. Steinbuks. 2017. “Assessing the Accuracy of Electricity Demand Forecasts in Developing Countries”, World Bank Policy Research Paper *7974*
  - J. Steinbuks, J. de Wit, A. Kochnakyan, and V. Foster. 2017. “Forecasting Electricity Demand: An Aid for Practitioners”, Live Wire No. 2017/73. World Bank, Washington, DC
  - A blog post on GSG Energy Economics internal blog