



Exploiting Demand Forecasting in Your Trading Strategies

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Improving your energy demand forecasting capabilities

Your goal: Energy trading with acceptable risk

Our topic: What you or your modellers need to take into account to minimise risk

Your takeaway: An understanding of how to evaluate what your demand forecasting system is delivering

Our credentials

The TESLA Power Forecasting System is in use at utilities serving 85% of the U.K. market, and at U.S. utilities with a combined peak load of over 140 GW

The TESLA Gas Forecasting System is in use at two of the "Big Six" U.K. gas suppliers, and on trial at two others

TESLA also supplies District Heat (CHP), Wind Generation and Outage Forecasting Systems, as well as models of most transmission zones in the European Union, US, Canada, Australia and New Zealand

Only a fundamental analysis of all market facets can minimise your trading risk

Power markets are affected by a complex mixture of causative factors:

- Weather
- Clock and calendar
- Behaviours and events
- Demographics and economics

Causative Factors: Weather

To achieve acceptable levels of accuracy in today's markets requires a full range of weather variables:

- Temperature
- Humidity
- Cloud cover (or insolation/solar radiation/light index)
- Wind speed
- Wind direction
- Precipitation (amount and type)

Causative Factors: Clock and Calendar

It is not enough to take into account the effect of different:

- hours of the day,
- days of the week, and
- seasons around the year

All the major effects (e.g. weather) have different impacts by hour, day of week and season, and by sun time

This means, effectively, that a largely distinct model has to be constructed for each hour, day of week and season

Causative Factors: Behaviour and Events

We need to model human expectations:

- Temperature is both a lagging and leading variable
- Humidity has more impact than the physics warrants

... and all facets of consumers' lives need to be considered:

- School holiday schedules
- Industrial shutdowns
- Special events (sporting events, minor festivals/holidays)

Causative Factors: Demographics and Economics

In the short-term, demographic and economic variables do not seem to matter. After all, they don't change quickly

But no model can be accurate without taking historical demographic and economic data into account

Since you have to take such information into account anyway, any good model should be able to serve as both a short-term and long-term tool

"Technical" methods do not reflect the complexities of energy markets

- "Technical" models aren't where you will make your money
- This is not to discount the value of pattern recognition used by a skilled trader on normal days
 - However, technical analysis gets completely neutralised on extreme days, when you are most exposed

Our philosophy: First avoid disasters, then think about the routine and recognisable stuff

Achieving excellence through innovative modelling and data management

Completeness of weather data and forecasts

Awareness of events occurring in the control area

Richly-specified models

Better demand forecasts = better price forecasts

Real-time feedback of weather, load and event data

Completeness of weather data and forecasts

Insist on what you need from your weather forecaster, and if you can't get it, switch forecasters

Forecasts should be updated hourly with actuals and a smoothed transition from actual to forecast

Weather forecasts delivered between midnight and 9AM need to be based on latest global model forecasts

Insist on a "best guess" on precipitation form, volume and timing

Getting a good weather set can be difficult

National meteorological offices are cutting back on the number of stations and the data that is collected

Much of the weather data collected is by far most useful to the energy sector. For example:

- Humidity does not play a large role in the physics of HVAC, but influences human behaviour greatly
- Night cloud cover is important, and the morning burnoff of marine cloud layers affects coastal loads drastically

...and a good weather forecast, even more difficult

Some meteorological offices and private weather forecasters are reluctant to forecast, for example, wind speed or rain

It is far harder to be correct in the details of those variables

To adequately forecast energy markets, push weather forecasters to forecast both easy and difficult variables

In return, though, do not judge them as strictly on these forecast variables as on temperature

Dense geographic meteorological coverage

For power or gas demands that cover even a modest area, models using a single weather station are inadequate

- Coastal models generally need:
 - wind direction, and
 - All weather variables measured at both the water's edge and inland at the population center
- All models benefit greatly from multiple stations' data on rain patterns

Awareness of events occurring in the control area

An ongoing effort must be made to track all events that significantly impact energy demand

- School schedules are key to predicting morning ramp-ups
- Large-industry production patterns must be monitored
- Major sporting events and television programming can have very large impacts

These are simple variables that are tedious to collect, but help to avoid large, expensive forecast errors

Richly-specified models

Energy demand is highly nonlinear, and exhibits persistence of error patterns over the short term

- Simple model specifications do not yield forecasts that are competitive in accuracy in today's markets
- Effects of all available weather measures and interaction effects among them are necessary
- Most of the error arising from overly simple models occurs at the extremes, where mistakes are costly

Better demand forecasts = better price forecasts

Price forecasting models are often sparsely specified with respect to weather effects

...or there is too much emphasis on detecting "patterns", which appear and disappear without warning

Using a richly-specified demand model, one can construct the ratio of demand forecasted using forecasted weather over demand forecasted using normal weather

Better demand forecasts = better price forecasts

The ratio of these demands gives an index number that reduces a complex weather situation into a single index number that represents the total effect of the weather on energy demand

This index number can serve as a powerful "total weather effects" variable that can be used in energy price models

This allows the implicit inclusion of far more weather information in price models than direct inclusion of comparable weather information

Real-time feedback of weather, load and event data

In a short-term trading environment, immediate access to information is crucial (especially in wind generation forecasting)

All vendors, all IT personnel, all reporting authorities (TSOs, settlement authorities, etc.) need to be pressed to get up-to-date data out quickly

Real-time feedback of weather, load and event data

Distribution loads reported with a three-day lag won't do
... even reported to last midnight won't do

Weather forecasts that are not updated overnight won't do
... and forecasts that don't react to the last hour's actual
observations won't do

And not talking to major industrial loads about their
production plans for the day, that *really* won't do

Evaluating short-term model and weather forecast accuracy

Multiple model approach

Assessing the quality of multiple models

Multiple model strategy – the blended approach

Checking weather data integrity

Measuring weather forecast accuracy

Multiple model approach

The richness of your model set should increase with your value-at-risk

You need the viewpoint of multiple models, created using differing techniques, assembled by different analysts

This is useful in assessing the range of likely outcomes...but perhaps more importantly, when your models diverge, that is a clear risk signal

Multiple model approach

However, this does not mean that you should add models without limit

If a model cannot beat your best model "head-to-head" at least 40% of the time, it probably should be dropped

Let's look at how many "avoidable bad beats" (from the normal part of the model's error distribution) can be averted by models with different levels of accuracy

Small differences in model "head-to-head" wins mean large opportunities for risk mitigation

Standard error of better model relative to inferior model	Percentage of time better model wins	"Avoidable bad beats" avoided by better model
Same	50%	0%
5% lower	51.6%	22%
10% lower	53.3%	41%
15% lower	55%	58%
20% lower	57%	71%
25% lower	59%	82%
30% lower	61%	90%

Assessing the quality of multiple models

Comparing energy demand models can be done in several obvious ways:

- "Equal playing field" (poor)
- "Best overall forecast" (useful, but not best)
- "Best backcast with actual weather data" (most useful)

Multiple model strategy – the blended approach

Constructing a composite forecast using a weighted average of forecasts from multiple models can be very valuable

A strategy for adjusting the weights over time is crucial

When using multiple models, the periods when the models disagree are important in their own right

In such periods, the optimal strategy is often to build a long position early and cheap

Multiple model strategy – the blended approach

Blending multiple model results with adaptive weights can sometimes give better results than any single model

... but including models in the blend that have a significantly higher error level will not yield a superior composite forecast

This approach is useful when distinct areas of strengths and weaknesses of various models have been identified

Multiple model strategy – the blended approach

A blended model needs to be continually assessed for accuracy against each of its constituent models

Blended model strategies, in our experience, are useful but overused; less accurate models are left in the blend when they should be deleted

Any individual model that does not outperform the best model *and* the blended model part of the time needs to be dropped

Checking weather data integrity

You cannot assess the quality of your weather forecast vendor if they don't report actual observations accurately

Accumulate actual weather data from your vendor and check it against national meteorological data

Don't tolerate the last forecasts of a given hour surviving as apparent actual data

If you use more than one vendor, cross-check that the actual observations reported are identical

Measuring weather forecast accuracy

The relative accuracy of forecasts of various weather variables is only part of what you need to measure:

- Expect forecasts of cloud cover, wind speed and precipitation to be less accurate

To compare more than one forecaster, focus on which one gives the better energy demand forecast:

- Weather forecast vendor accuracy figures are hard to assess, while megawatts of error are not

Weather correction and other tools for long-term energy demand forecasting

Weather correction for:

- weather and revenue normalisation
- weather dimensionality reduction
- decomposition of weather effects

Monte Carlo analysis with actual weather strips

Load curve deformation over time

Weather correction: For weather and revenue normalisation

Weather correction removes weather effects from load

- The total weather effect is the backcast using actual weather less the backcast using normal weather
- Subtracting this from actual load gives the weather-corrected load



The weather-corrected load is not the same as the backcast using normal weather

Weather correction: For weather and revenue normalisation

Weather-corrected demand tells you if the service territory is actually growing or declining

It is an important part of long-term demand forecasting

For any energy company with obligations to serve a service territory or a retail portfolio, weather-corrected demand is central to revenue forecasting

Weather correction: For weather dimensionality reduction

An alternate way of stating weather correction is the "weather adjustment ratio", which is the ratio of actual historical load to the weather-corrected load

This ratio is a proxy for the full set of variables for all weather stations used by the model

As such, it can serve as a single-variable proxy for all weather effects in price forecasting models

Weather correction: For decomposition of weather effects

The total weather effect can be separated into effects arising from temperature, wind speed and all the other weather variables

- This allows weather derivative-based hedging to be done against uncertainty in the proper variable(s)
- Why hedge the wind effect using a temperature-denominated trading instrument?

Monte Carlo analysis with actual weather strips

Confidence bands for demand forecasts are difficult to establish parametrically

- The true confidence band varies by time and day type
- The statistical errors in load forecasts are non-normal
- But most seriously, confidence bands are not symmetric

Some form of Monte Carlo analysis is the best way to assess the actual distribution of likely outcomes

Monte Carlo analysis with actual weather strips

Monte Carlo analysis with weather simulation systems can give very misleading results

It is difficult to calibrate a weather simulation to multiple weather stations, and to make sure that simulations of multiple stations give sequences that could actually all happen at the same time

Monte Carlo analysis with actual weather strips

You need to extract sequences of actual weather data from the past history of each weather station, and avoid use of weather simulations entirely

- 30 years of history shifted +7 to -7 days gives 450 replications that actually happened
- The confidence bands produced are generally broader than with other techniques, reflecting that other methods generally understate the risk that you face

Load curve deformation over time

In any hourly, sub-hourly or other intra-day model of demand, provision must be made for the load shape to change over time

- Demand models are estimated on large volumes of data stretching over several years. The structure of the demand won't be stationary over that length of time
- ... and this applies not just to shifts in demand level by time of day, but to all weather and calendar effects

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