

## Paper 4743-2020

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## ABSTRACT

Forecasting power prices can be more of an art than it is a science. Locational Marginal Prices (LMPs) exhibit high volatility—a phenomenon known as volatility clustering as with many financial time series data. This paper will not discuss the mean reverting properties of power prices and assumes the reader has a basic understanding of the autoregressive nature of electricity prices. This method forecasts LMPs by preserving past volatility in the form of ratios and assigning them to corresponding load in the forecast. The purpose is to “shape” the forecasted series by utilizing historical profiles while holding to supply and demand fundamentals—high electricity usage *tends* to be associated with higher energy prices.

## INTRODUCTION

Great importance is given to forecasting energy prices especially at the hourly level. Power plants dispatch and make on and off decisions based on an hourly energy price commonly referred to as Locational Marginal Price (LMP). This example will demonstrate how to forecast and shape hourly LMPs from a given peak, off-peak, and weekend *monthly* price. The challenge with simply converting a monthly price to hourly is that it overlooks the uniqueness of the LMP at every hour, thereby repeating the price and making the forecast unreasonable. Developing historical relationships (ratios) of the LMP to its monthly average is key to shaping the forecast. To correlate the calculated ratios to load, one needs to rank daily load and assign the LMPs to its corresponding ranks in the future forecast.

## HISTORICAL RATIOS AND LOAD RANKS

For simplicity, the one-year profile used historical hourly prices and load to develop ratios used in the forecast. This example assumes you have a vertical hourly dataset of LMPs and load from an RTO. Our first step is to create sub periods that correspond to peak, off-peak, and weekend periods. Then run the means procedure to get averages by month for each sub period (I.e., WD, WN, WE).

SAS code for creating sub periods and ratios (e.g. WD (Peak), WN (Off-Peak), WE (Weekend));

```
data _null_;
  set hist_lmp_load;
select;
          /* Peak (WD) 5 days x 16 hours*/
  when(weekday in('MON','TUE','WED','THU','FRI') and hour
in(7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22))
  do;
wd=1; /*peak*/
wn=0;
we=0;
end;
```

```

when(weekday in('MON','TUE','WED','THU','FRI','SAT','SUN')and hour
in(1,2,3,4,5,6,23,24))
do;
wd=0;
wn=1; /*off-peak*/
we=0;
end;

when(weekday in('SAT','SUN')and hour
in(7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22))
do;
wd=0;
wn=0;
we=1; /*weekend*/
end;

otherwise;
end;
run;

data _null_; /*calculate ratios*/
set hist_lmp_load;
if wd=1 then do;
ratio=price/wd_mo_avg;
end;
if wn=1 then do;
ratio=price/wn_mo_avg;
end;
if we=1 then do;
ratio=price/we_mo_avg;
end;
run;

```

## LOAD RANKING

The last step in setting up the historical dataset is to rank the load by Peak and Off-peak in descending order so that rank one is the highest value. Each month will have approximately 23 peak and 7 off-peak days. Below is a small sample of the output for peak. Repeat the process for Off-Peak. In our January example, peak ranks are 1-21 and off-peak are 1-10 totaling 31.

Month	Day	Type	LOAD	RANK
1	8	PEAK	171,357	1
1	9	PEAK	159,710	2
1	7	PEAK	159,127	3

**Table 1. Daily load ranked by month, peak, and off-peak.**

## CREATING THE HOURLY FORECAST

The second dataset is the generic hourly forecast for January. The first task in the in creating the forecast is to transform prices from monthly to hourly and create subperiods (e.g. WD, WN, WE) as done in the previous section. The second piece of data that is an hourly load forecast from an RTO that corresponds to January 2020.

Year	Month	Peak	Off-Peak	Weekend
2020	1	26.45	24.78	19.37

1. Transform prices to hourly.
2. Create weekday, weeknight, and weekend sub periods and define peak and off-peak periods from the "Forecast."
3. Rank the forecasted load by month, day, and type (peak, off-peak).
4. Lastly, join the forecast with historical table by rank, month, and hour.
5. Multiplying the forecasted hourly LMP by the ratio will produce the simulated LMP. Once calculated, the monthly averages (e.g. Peak, Off-Peak, and Weekend) should match the prices given above for January 2020.

## CONCLUSION

There are many methods for calculating and forecasting LMPs. This example focused on forecasting hourly energy prices when given a forecasted monthly price. Again, simply transforming a monthly to an hourly energy price undermines the volatility and uniqueness of hourly energy prices. Correlating ratios (volatility) to load gives the forecast a shape that is representative of its historical pattern making it more reasonable by assigning LMPs with its paired load ranking.

## CONTACT INFORMATION

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