

Weather Contingent Load Simulation

By Carlos Blanco, Josh Gray and Marc Hazzard

Introduction

This article is the second in a multi-article series on the FEA Power Sector Model. The first article provided an overview of the issues that must be confronted in the realistic modeling of power prices and the valuation of generation assets and load contracts. We proposed a hybrid model to incorporate weather, load, and fuel factors in the stochastic evolution of power prices.

Building on the momentum in the first article, while simultaneously taking a step back to survey, we will now focus in on the calibration and simulation of hourly load values. While long acknowledged as load's fundamental driver, weather is usually only implicitly accounted for in most load simulations. In our simulation and calibration framework, weather is explicitly linked to load dynamics.

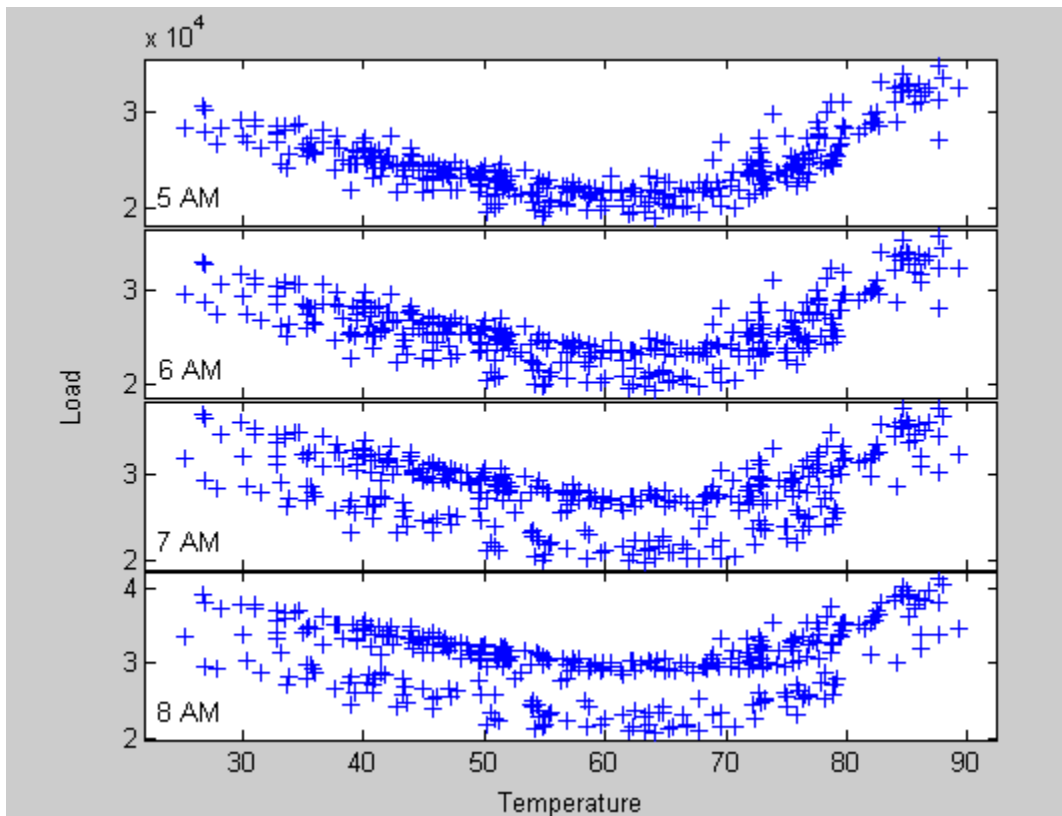


Figure 1: Philadelphia temperature versus load, for various off- and on-peak hours



Weather Simulation

While the calibration of weather models using historical data is rife with challenges (Dischel 1998), anchoring any simulation of load to a simulation of weather is a natural step forward in the modeling process. Aside from being the fundamental driver of load in most generation regions, it gives the conditional distribution of load a stationary characteristic. We can also draw upon our experience calculating weather-contingent claims and bring to bear a vetted, tested weather model. Given the proper care and treatment, the vast quantity of historical weather data can be used to the advantage of the energy modeler.

An added benefit of simulating weather, load and prices simultaneously is the possibility of calculating the value of contingent claims dependent on the weather and other variables simultaneously (e.g. double triggers, triple triggers...).

A Stochastic Model for Weather

The FEA Power Sector models weather by specifying a mean-reverting, normally-distributed process with a time-dependent mean reversion level for the weather variable. This mean-reversion rate determines the speed at which daily weather is returning to the mean level. Additionally, time-dependent volatility levels determine the variability of the expected changes in weather over the course of a month.

These model parameters can be easily calibrated from a set of historical daily average temperatures using maximum likelihood methods. We can also bring forward-looking estimates such as the expected average weather patterns. The mean reversion levels and volatilities represent the seasonal behavior of temperature, which then drives the seasonal behavior of load. Mean-reversion is an important characteristic of the model since temperature is generally expected to display a mean-reversion time of a few days, in agreement with our experience with transient weather patterns.

Figure 2 represents the long-term pattern of weather, using high, low and average temperatures for Denver. The darker lines indicate the calibrated mean-temperature levels and seasonal volatility fluctuations. A simulation of these variables would also need a calibrated mean-reversion rate.

Denver temperature '82-'01

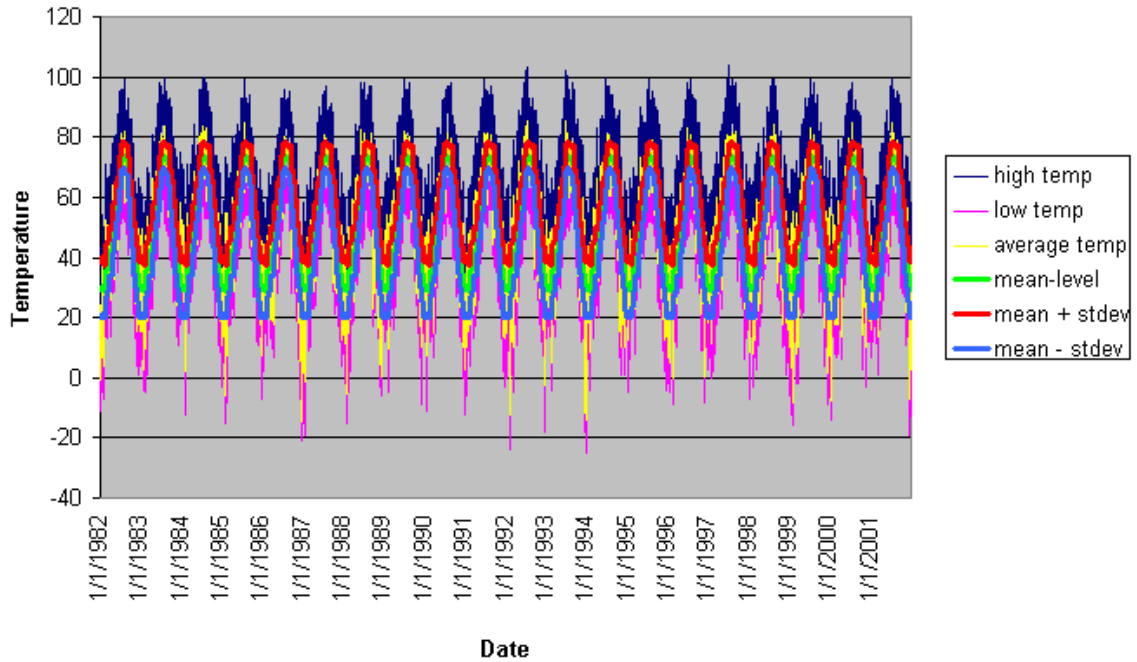


Figure 2: Denver Historical and Calibrated Temperature Levels

In order to simplify the analysis, we can calibrate hourly load patterns using average daily weather data. It can be argued that the load response is a function of average temperature, since temperature usually does not “spike” or “jump” intra-day. The shape of temperatures during each hour is then preserved or “contained” in the average. This assumption also avoids far more challenging data collection and cleaning problem that comes with the requirement of an hourly temperature process. In Figure 3, we offer a blow-up of the 10-year pattern suggested in Figure 2, which also motivates the usage of the average temperature as a weather indicator.

Denver temperature 2001

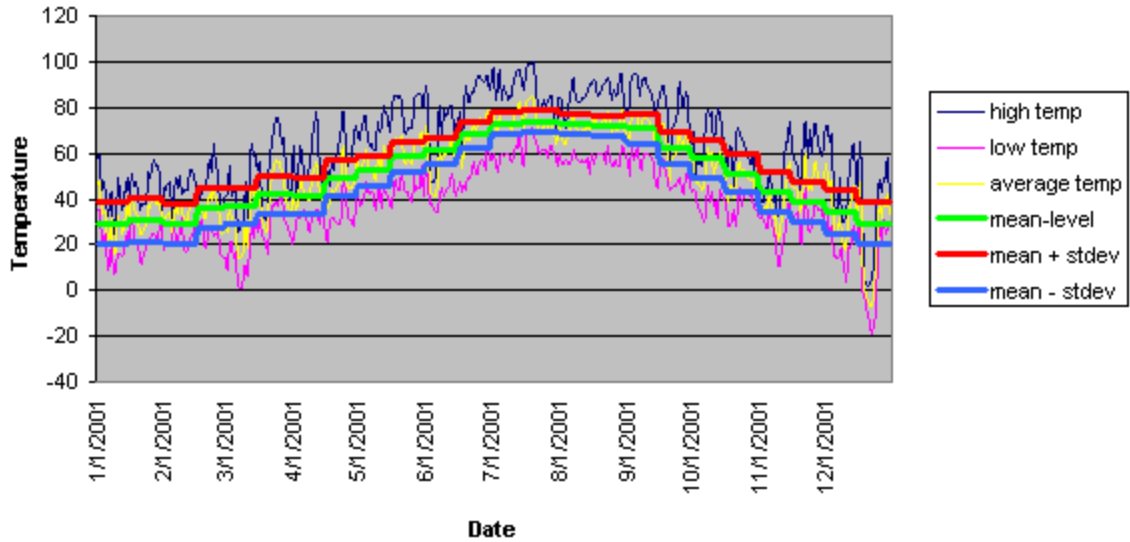
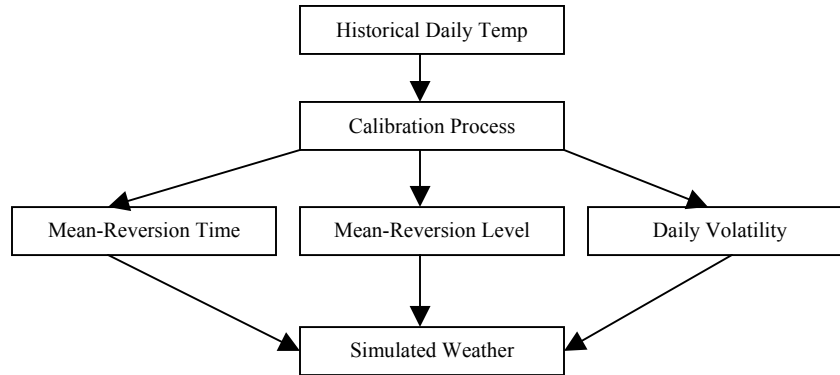


Figure 3: Denver 2001 Historical and Calibrated Temperature Levels

Weather Simulation Process



Load Calibration and Weather-dependent Simulation

Load tends to follow weather patterns. If we analyze historical hourly load data, we can see that certain patterns tend to emerge. For example, load patterns are conditional on the average temperature range for each day, whether it is a business or non-business day, and what is the hour of occurrence. The transient nature of the historical load pattern is illustrated in Figure 4, for one-year of Philadelphia on-peak load data.

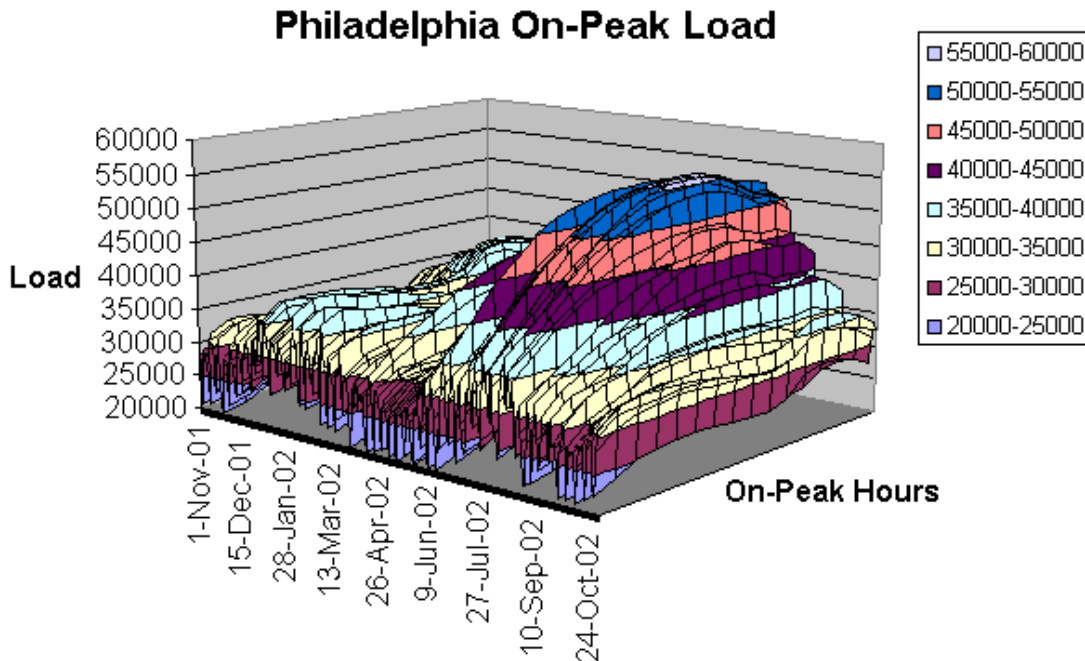


Figure 4: 3D plot of load levels throughout the year for on-peak hours

In order to extract meaningful load patterns that can be used in our simulation pattern, we can group the load data in temperature bins, and analyze their behavior within each of those blocks. After simulation of the underlying weather levels, the load is then calculated conditional on that weather level. Figure 5 presents an hour-by-hour Power Sector calibration of the load to temperature surface. Notice the characteristic “smile” shape of the load profile, when viewed from the left-hand side, reminiscent of the patterns of Figure 1.

Calibrated Hourly Load to Temperature Relation

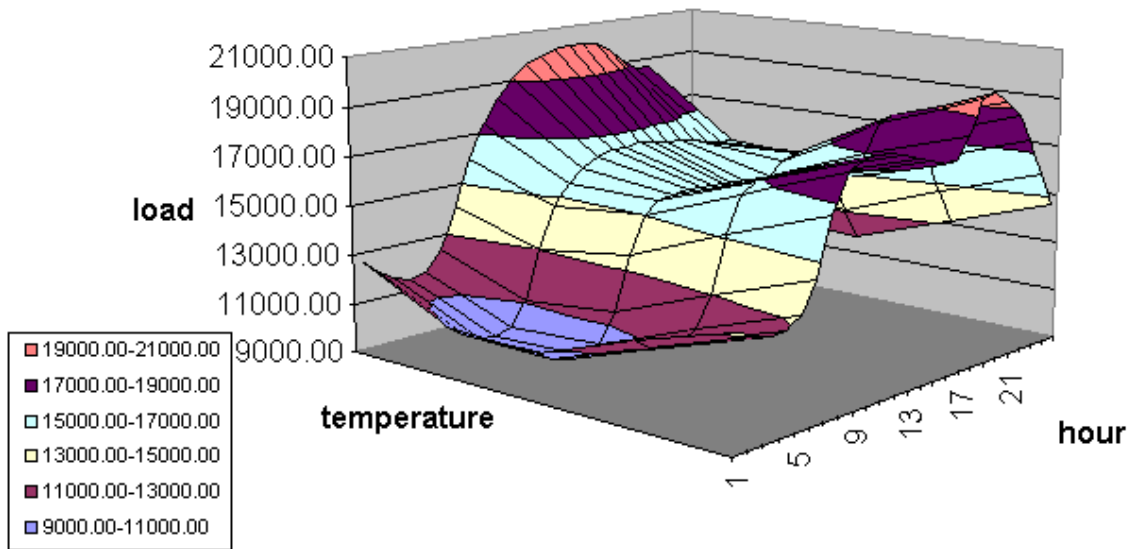


Figure 5: surface plot of hourly load levels for each temperature bin

Historical load fluctuations can be explained using different methodologies. Regardless of the chosen methodology, the main objective is to be able to calibrate the parameters that determine load fluctuations at an hourly granularity. In particular, we need to extract average load levels for each hour, expected variability and expected co-movement with the load for other hours of the day around a historically averaged load contingent upon an average temperature.

In order to simulate weather and load simultaneously, we can first simulate weather levels, and contingent on those weather realizations, we can determine the appropriate calibrated parameters that reflect the “state-of-the-world” for which we need to simulate load patterns.

Principal Components Analysis and Co-movements in Hourly Load

An elegant and robust way to extract and simulate weather and load fluctuations is through Seasonal Principal Components Analysis (PCA), a technique that can substantially reduce the dimensionality of the problem and explain the variance of load changes in a parsimonious manner. A more detailed explanation of PCA can be found in earlier works (Blanco, Stefiszyn 2002).

At the heart of PCA is the desire to both remove spurious correlation measurement and speed up computation time by not having to use the full variance-covariance matrix of hourly load. If we were trying to explain hourly load fluctuations, we would need a 24x24 matrix. A principal component analysis can usually find 4 or 5 “factors” that explain well over 99% of the variance. These factors, and their associated factor loadings – which describe how shocks are propagated into the 24 hourly prices - are then used to

simulate load as a random variable. Since this analysis is inherently a multi-factor analysis, it can more ably capture the full dynamics of load shapes.

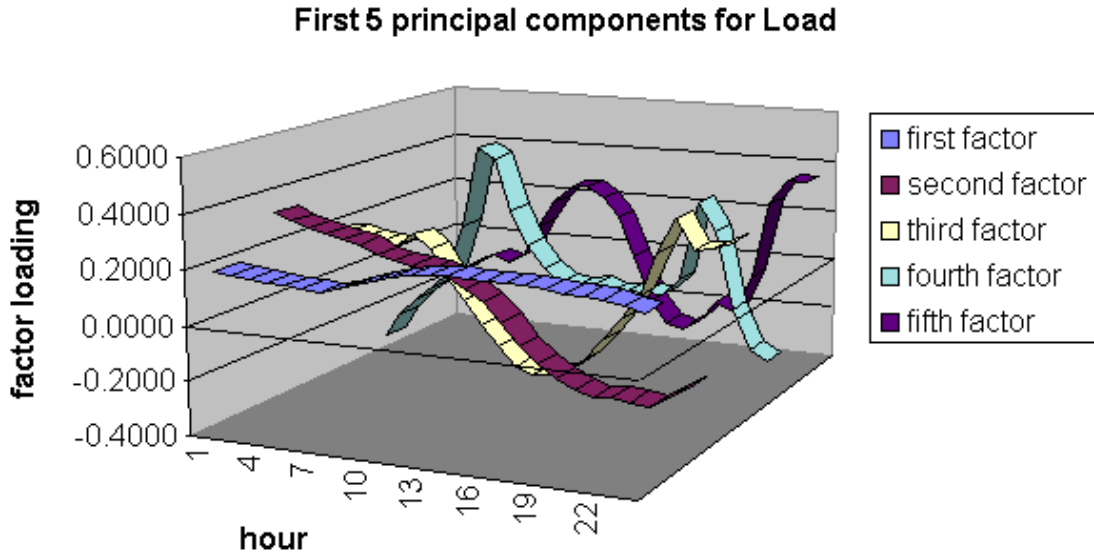


Figure 6: Graphic depiction of first 5 principal components of hourly load variance-covariance matrix

Typically, we find that the first component describes an approximately parallel shift to the 24 hourly loads. The second component demonstrates a split between the pre-noon, and afternoon load, in particular, that the afternoon loads' perturbation are opposite to that of the morning load. These qualitative features are shown in Figure 6.

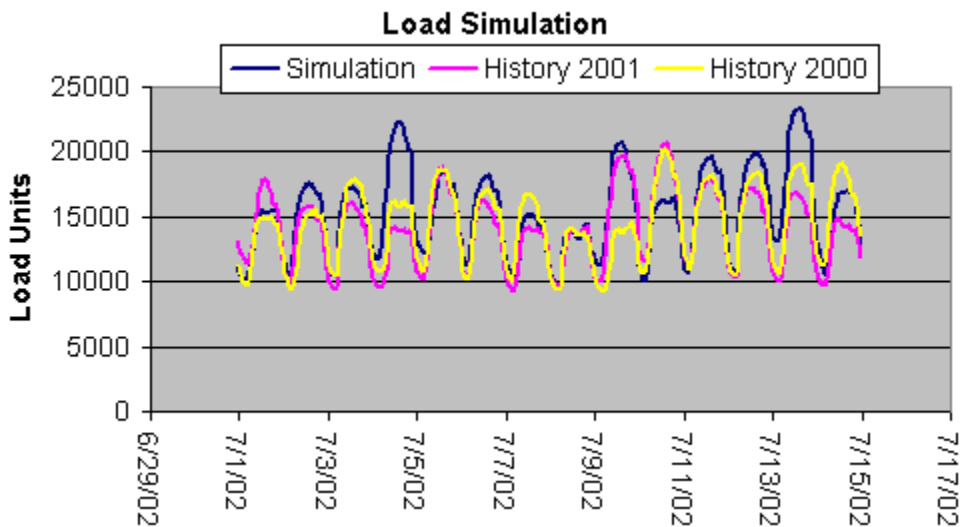
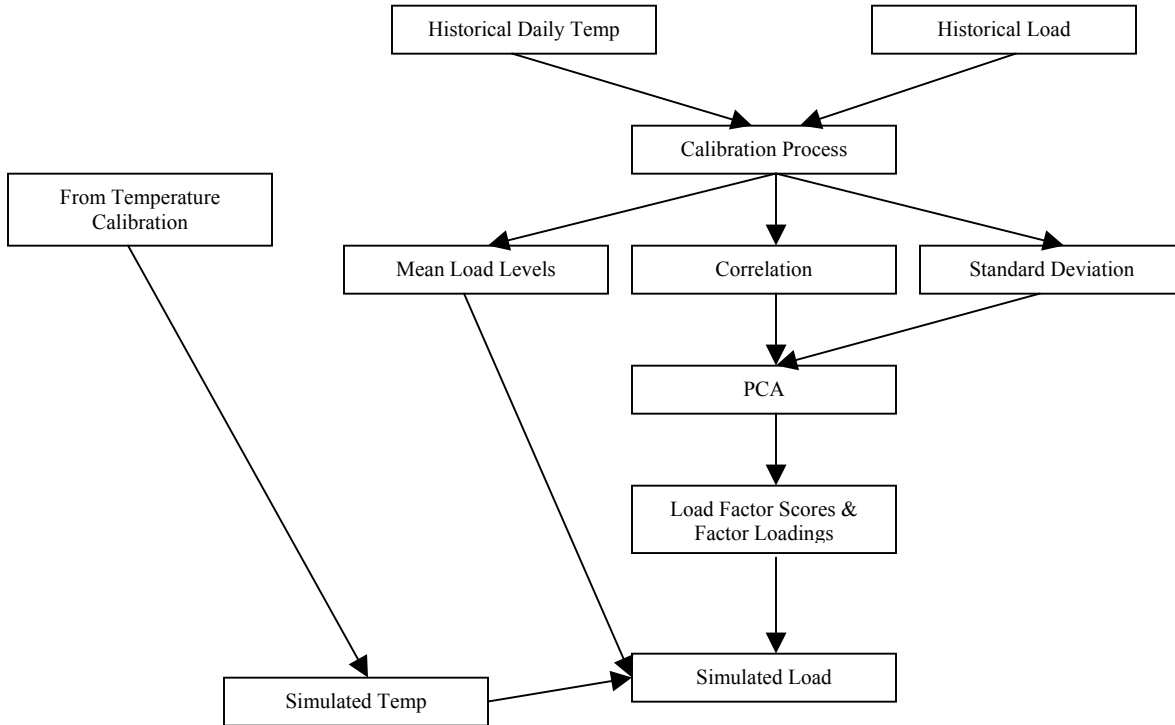


Figure 7: Hourly Load: Historic versus Power Sector Simulation

Load Simulation Process



Conclusion

Although the estimation of a future load distribution is at best an uncertain exercise, empirical evidence shows that doing such an estimation in a weather context improves our results. The stationary nature of weather phenomena grounds our hourly load simulation in both history and nature. FEA's Power Sector, by treating the load-weather pair as one construct, offers advantages over load "forecasting" en route to specifying the load distribution for further use in energy derivatives modeling.

Bibliography

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