REDACTED
Docket No. UE-227
Exhibit PPL/702
Witness: Frank C. Graves

BEFORE THE PUBLIC UTILITY COMMISSION

OF THE STATE OF OREGON

PACIFICORP

Redacted Exhibit Accompanying Surrebuttal Testimony of Frank C. Graves

Appendix A – Estimating the Volatility Term Structure

August 2011

APPENDIX A: ESTIMATING THE VOLATILITY TERM STRUCTURE

Appendix A explains how I obtain the components of the volatility term structure such as the near-term, the long-term and the seasonal volatility. I obtained broker quotes from the Company on volatilities and then estimated the components of the volatility term structure, which determine the relationship between volatility, quote date, and delivery time. These quoted volatilities are derived from (or implied by) a standard financial model, the Black-Scholes option model for pricing options on gas futures. Figure FCG-A1 below presents one such set of quotes as they described the market for gas contracts at RockOpal at the beginning of October 2007.

Figure FCG-A1

[redacted]

These volatilities will change over time, but they also have some patterns or recurring structure. Typically, the term structure of annualized volatilities is declining, whereby the high, near-term volatility decays to a steadier lower long-term volatility. The decline occurs because many near term risks generally do not affect the long term. While near term risks reflect current market conditions, the long term risk is more a reflection of beliefs about long run marginal costs. This does not mean that there is less cumulative risk in the long run than in the short run. Instead, the declining shape indicates how much the forward price of a given delivery month is likely to change over the coming month, not how much it could change over the entire time to delivery. This higher sensitivity to short run risks also means that the volatility quoted for a given month, say September, will depend on how far ahead in time September is at the time of the quote. Finally, there are seasonal variations in risk corresponding to different typical supply and demand conditions of the market.

All of these patterns can be seen in Figure FCG – A1. It is clear from the figure that the volatility declines over time, so that the near-term volatility is much larger than the more distant volatility. The bumps along the way reflect seasonality.

The declining term structure, seasonality, and sensitivity to pending time to delivery, can be used to compare risk conditions over time. However, in order to evaluate how volatility expectations in the market have changed over time, the broker quotes must be normalized for seasonality and time to delivery. I have done this by fitting an exponentially declining curve with monthly seasonality to the quoted volatilities, so that the squared error (the difference between the estimated and the actual volatility) is as small as possible. The separation of the short and long term factors from the seasonality also allows me to compare volatilities over time in a manner that is not feasible with the raw volatility quotes (which would be confounded by differences in dates of purchase).[1]

The process of estimating the components of the volatility curves is best illustrated in steps. First, I determine the declining exponential curve that best fits the quoted volatility. This is shown in Figure FCG – A2 below, where the red curve indicates the best fitting curve.

[1] See for example, Chapter 8 in L. Clewlow and C. Strickland (2000), "Energy Derivatives: pricing and Risk Management" and Electric Power Research Institute (EPRI) Technical Brief W03581 for a derivation of the mathematics of this approach.

Figure FCG – A2

[redacted]

To obtain the fitted curve in Figure FCG – A2, I estimated the near-term and the long-term volatility. The near-term volatility is initial volatility at the y-axis, while the long-term volatility is the volatility in distant future. I will focus on how these parameters changed over the time frame from mid-2007 to late 2009 in my analysis of risk expectations facing PacifiCorp.

In addition to the exponentially declining pattern in the quoted volatility, there is also a series of bumps along the path, which are month-to-month or seasonal effects. To determine the effect of the monthly seasonality, I estimated monthly seasonality factors, which are expressed as a percentage of the overall volatility, so that a coefficient of 100% indicates no seasonality, while a higher coefficient indicates a relatively higher volatility during that month. Figure FCG – A3 below illustrates the effect of adding monthly seasonality factors to the fitted curve. As can be seen from the figure, the fit improves substantially when seasonality it taken into account.

Figure FCG – A3

[redacted]

Going through these steps results in an estimate of the short-term, long-term and seasonal volatilities, which can be used to evaluate the risk conditions and the development in risk conditions over time.

In addition to improving the statistical fit, the monthly coefficients are useful for understanding whether certain delivery months have more or less risk than others. The table below summarizes these coefficients for all the volatility series I evaluated. The last three rows of this table show the averages and the range of values within any given month. The variation is fairly modest. Winter months tend to have slightly higher volatility, while the spring months are the lowest, but only about 93% on average of the non-seasonalized volatility.

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